Neural Reverse Engineering of Stripped Binaries

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Abstract
We address the problem of predicting procedure names in stripped executables which contain no debug information. Predicting procedure names can dramatically ease the task of reverse engineering, saving precious time and human effort.

We present a novel approach that leverages static analysis of binaries with encoder-decoder-based neural networks. The main idea is to use static analysis to obtain enriched representations of API call sites; encode a set of sequences of these call sites; and finally, attend to the encoded sequences while decoding the target name token-by-token.

We evaluate our model by predicting procedure names over 60,000 procedures in 10,000 stripped executables. Our model achieves 81.70 precision and 80.12 recall in predicting procedure names within GNU packages, and 55.48 precision and 51.31 recall in a diverse, cross-package, dataset. Comparing to previous approaches, the predictions made by our model are much more accurate and informative.

1 Introduction
Reverse engineering (RE) of executables has a variety of applications such as improving and debugging legacy programs. Further, it is crucial to analyzing malware. Despite great progress on disassemblers [5, 8], static analysis frameworks [33, 35] and similarity detectors [25, 42], the reverse engineering process remains mostly manual. Unfortunately, it is a hard skill to learn which takes years to master, and even experienced professionals often have to invest long hours to obtain meaningful results.

Reverse engineering a given executable is a tedious and time-consuming task. A human reverse-engineer has to guess (usually based on experience) the more interesting procedures to begin with, follow the flow in these procedures, find connections between procedures, use inter-procedural patterns and finally piece all these together to get a global understanding of the purpose and usage of the inspected executable.

The main challenge in reverse engineering a binary executable is understanding how the different “working parts” inside it are meant to interact to carry out the objective of the executable. Automatically labeling procedures in the binary with meaningful names dramatically reduces human effort, as it saves the time and effort of looking at some procedure bodies [14, 28, 31, 32].

In recent years, great strides were made in the analysis of source code using learned models. From automatic inference of variables and types [10, 15, 19, 20, 46] to bug detection [43, 49], code summarization [11, 13, 14], code retrieval [12, 52] and even code generation [21, 37, 41]. In this work, we propose a neural learning approach for reasoning about compiled assembly code. To the best of our knowledge, this is the first work to leverage deep learning for reverse engineering procedure names in the domain of Reverse Engineering (RE).

Problem definition Given a nameless assembly procedure \( X \) residing in a stripped (containing no debug information) executable, our goal is to predict a likely and descriptive name \( Y = y_1, \ldots, y_m \), where \( y_1, \ldots, y_m \) are the subtokens composing \( Y \). Thus, our goal is to model \( P(Y \mid X) \). For example, for the name \( Y = \text{create_server_socket} \), the subtokens \( y_1, \ldots, y_m \) that we aim to predict are \( \text{create}, \text{server} \) and \( \text{socket} \), respectively.

The problem of predicting a meaningful name for a given procedure can be viewed as a translation task – translating from assembly code to natural language. While this high-level view of the problem is shared with previous work (e.g., [11, 13, 14]), the technical challenges are vastly different due to different characteristic of binaries.

Challenge 1: Little syntactic information Assembly code from a stripped executable is a sequence of instructions lacking variable names (see for example the disassembled block in Figure 1.a). Learning descriptive names for such a low-level stripped representation is a challenging task. A naive approach where the sequence of instructions is fed into a seq2seq architecture [38, 56] yields hopelessly imprecise results (37.52 F1 score, as we show in Section 7).

Challenge 2: Long procedure names Procedure names in compiled C code are often long, as they encode information that would be part of a typed function signature in a higher-level language (e.g., \texttt{AccessCheckByTypeResultListAndAuditAlarmByHandleA} in the Win32 API). This means that methods which attempt to directly predict a full label as a single word from a vocabulary will be imprecise. As we show in the ablation study of Section 7, without a sequential decoder, F1 score drops from 53% to 33%.

Our approach We present a novel end-to-end system that generates a descriptive name for a given stripped assembly procedure. Towards this end, we combine: (i) a novel and effective representation for assembly code which reconstructs sufficient information to feed into a learning pipeline. This representation is based on sequences of \texttt{reconstructed} call
(ii) a novel neural architecture, based on the encoder-decoder paradigm, where the encoder works on a set of reconstructed call site sequences, and the decoder attends over their representation.

This combination provides an interesting and powerful balance between the program-analysis effort required to obtain the representation from executables, and the effectiveness of the learning step. We demonstrate the effectiveness of the approach as a whole in Section 7.

**Main contributions**

The main contributions of this work are:

- A novel representation for binary procedures. This representation is based on reconstructed call site sequences in the Control Flow Graph (CFG) and is tailored to procedure name prediction. This representation is imperative to connecting call site paths in the procedure with its name.

- A novel neural architecture, based on the encoder-decoder paradigm [56], that effectively encodes sequences of call sites and attends to them to accurately decode procedure names in stripped binaries. To the best of our knowledge, our work is the first to use neural networks for reverse engineering procedure names in stripped binaries.

- A full system called Nero for binary name prediction composed of: (i) A crawling and compilation framework for generating a dataset, (ii) a binary analyzer for reconstructing call site sequences from executables, and (iii) a neural network for generating and evaluating name prediction.

- We demonstrate that our system can be used to accurately predict names for real-world Linux applications. Our model achieves F1 score of 80.9 in predicting procedure names within GNU packages, and F1 score of 53.3 in a diverse, cross-package, dataset. Comparing to previous approaches, the predictions made by our model are much more accurate and informative.

## 2 Overview

In this section, we illustrate our approach informally and further explain the challenges in binary procedure name prediction using an example.

### Using Imported Procedures for Name Prediction

Given a binary procedure, our goal is to suggest a meaningful and likely name that describes its purpose. We focus our example on the Intel 64-bit executables running on the Linux Operating System (OS), but the same process can be applied to other architectures and OS’s. We draw our initial intuition from the way a human reverse engineer skims the code of an unknown procedure \( P \), stripped from debug symbols. After disassembling \( P \)’s code, one can see a flow of instructions such as the ones shown in Figure 1(a). This example is a real-world unseen example from our test set, which the model did not observe nor had access to during training.

To understand what this code snippet does, the most helpful pieces of information are calls to procedures which were dynamically linked to the examined executable. Such calls are demonstrated in the case of `call getaddrinfo` at line 8 and `call setsockopt` at line 17 in Figure 1(a). These API names, along with the list of libraries loaded before execution, cannot be stripped without breaking the loading process; stripping them would leave the executable unusable. For the same reason, if the examined executable is a library, procedures exported by the library cannot be stripped either.

Examining debug-symbols for libraries used by the executable, we retrieve the number of arguments passed to each procedure. Following the calling conventions we map each argument to the register used to pass this argument (for brevity we will not go into stack-passed and float arguments). Finally, we arrive at a construct very similar to a call site in higher-level computer languages, as shown in Fig. 1(b) where each API name is matched with the names of the registers it takes their values as arguments.

To further enrich the information stored in these call sites we look for the value stored in each register used as an argument. This information can be gathered only by analyzing...
the calls in the context of the entire procedure. To gather this information, we compute a static slice of each register at the call location in the procedure. A slice of a program [57] at a specific location \( l \) for a specific value \( x \) is a subset of the program’s instructions necessary to create the value of \( x \) at location \( l \). This process is explained in Sec. 6.1

Each register at the call location in Fig. 1(b) is connected by an arrow to the slice of \( P \) used to create its value. For example, the value of \( rsi \) for the setsockopt call was created by an assignment of a constant value 1. In a more complex case, the value of \( rcx \) used for the same call was created by putting the constant value of 1 on the stack, and passing its pointer—obtained using the “load effective address” instruction lea.

**Extracting Paths of Abstracted-Call-Paths** In some cases, procedure arguments are Enums. As such, the specific constant value used carries a special meaning that directs the semantics of the called procedure. One example is the value of 1 for \( rcx \) in the setsockopt call mentioned before; this maps to the level argument for which, in this case, the Enum value for 1 is IPPROTO_TCP. In other cases, the specific values passed only hint to the purpose of the call, such as the size of buffer to allocate in malloc, or the fact that the value to write using memset is 0. An example for one such case is presented later in this section.

In the rest of the cases, the meaning or value of a specific register is unknown. One such case is the value of \( rdi \) passed to setsockopt, which is the result of call to the socket procedure. Another such case is that of \( rdi \) used in getaddrinfo which is the argument passed into \( P \), coincidently by using \( rdi \) as well. Finally, the values of \( rdx \) and \( rcx \) are just pointers to structures allocated on the stack.

These cases show the need to find a suitable representation for values used as arguments in calls. We need a representation that allows us to encode some of the surrounding computation related to external procedure calls, but is compact enough not to burden or over-complicate our analysis. For our problem, we decided to analyze each argument register slice and classify these into one of 5 groups: argument (ARG), locally created value (VAL), global value (GLOBAL), and unknown constant value (CONST). When a specific value can be extracted, e.g., the number “1”, it is used as-is without classifying it. We call these classes argument kinds. Complete details regarding this representation are presented in Section 4.

Finding argument kinds for the two procedure calls in Figure 1(b) results in getaddrinfo \( (\text{ARG,ARG,CONST,CONST}) \) and setsockopt \( (\text{VAL,1,2,CONST,4}) \).

After reconstructing call sites, we examine the way these calls are used in \( P \). To this end, we explore \( P \)’s CFG. The paths in \( P \)’s CFG show how the various calls are strung together into a sequence, expressing the desired functionality. Figure 1(c) shows the CFG containing only our call sites. Using the edge numbers, we see that this CFG contain four distinct sequences:

(1, 2), (1, 3, 4), (1, 3, 5, 6), and (1, 3, 5, 7, 8). Figure 1(d) shows these sequences after extraction.

This representation makes it easier to reason about the behavior of the procedure, both for a human reverse engineer, but also for automatic tools. For example, following the longest path:

- The procedure allocates a zero-filled 48-bytes structure on the stack, as can be deduced from memset \( \text{(CONST,0,48)} \).
- This structure size, in the context of the rest of the APIs used in this procedure, suggests that this structure will hold the addrinfo structure used in the next API call.
- The getaddrinfo API searches for network interfaces available on the host abiding to specific constraints provided by the first three arguments passed to it. Examining the call site information getaddrinfo \( \text{(ARG,ARG,CONST,CONST)} \), we see that two of \( P \)’s arguments are used, alongside an unknown constant expression created inside the procedure, to guide the search for a suitable network interface. The last argument to getaddrinfo is a pointer to a memory block to store the result on.
- After the interface is found, a socket is created: socket \( \text{(CONST,CONST,CONST)} \). The socket is then configured using setsockopt \( \text{(VAL,1,2,CONST,4)} \). The first argument to setsockopt is a file descriptor created by the socket call, represented by the VAL kind. The rest of the arguments define the configuration of the socket. Most importantly, the level argument, with the static value 1, makes the socket a TCP socket.
- Following calls to bind and listen, for which argument kinds were redacted for brevity, determine that this procedure creates a socket used as a server listening for incoming clients.

The rest of the calls are made to handle and report errors (strerror) in its creation and cleaning up created resources (close and freeaddrinfo).

A human reverse engineer examining these call site sequences may rename it to open_socket. Indeed, as shown in Figure 1(d), our model attended mostly to the longest sequence during all decoding steps (attention weight shown inside the stars), and automatically predicted the name create server socket (Figure 1(e)).

It is important to note that the exact attended sequence of call sites has not been observed in the training set; this motivates a neural model that can leverage unseen sequences by generalizing only small parts of it.

**Key aspects** The illustrated example highlights several key aspects of our approach:

- Using static analysis, API call sites can be reconstructed from the shallow assembly code.
- Useful information about the kinds of the passed arguments can be reconstructed by analyzing the values stored in the registers.
3 Background

In this section we provide necessary background. In Section 3.1 we describe the encoder-decoder paradigm which is the basis for most seq2seq models; in Section 3.2 we describe the mechanism of attention.

3.1 The Encode-Decoder Paradigm

Contemporary seq2seq models are usually based on the encoder-decoder paradigm [23, 56], where the encoder maps a sequence of input symbols \( x = (x_1, ..., x_n) \) to a sequence of latent vector representations \( z = (z_1, ..., z_n) \). Given \( z \), the decoder predicts a sequence of output symbols \( y = (y_1, ..., y_m) \), thus modeling the conditional probability: \( p( y_1, ..., y_m | x_1, ..., x_n ) \). At each decoding time step, the model predicts the next symbol conditioned on the previously predicted symbol, hence the probability of the target sequence can be factorized as:

\[
p(y_1, ..., y_m | x_1, ..., x_n) = \prod_{j=1}^{m} p(y_j | y_{<j}, z_1, ..., z_n)
\]

Key components in these models are RNNs, and typically LSTMs [30], which are neural network components that are trained to accept a sequence of input vectors, and return a sequence of output vectors, based on internal learned weight matrices. Throughout processing the input sequence, the LSTM keeps an internal state vector that is updated after reading each input vector. The encoder maps the input symbols \( x = (x_1, ..., x_n) \) to a sequence of latent vector representations \( z = (z_1, ..., z_n) \). Typically [23, 56], this mapping is implemented by an LSTM. The decoder can also use an LSTM and an aggregation of encoder LSTM states as its initial state. Traditionally, the decoder’s initial states are initialized by the final hidden states of the encoder’s LSTM:

\[
h^\text{enc}_1, ..., h^\text{enc}_n = \text{LSTM}_{\text{encoder}} (x_1, ..., x_n)
\]

The decoder contains separate LSTMs that have their own internal weights and state vector. At each decoding step, the decoder reads a target symbol and outputs its own state vector \( h^\text{dec}_t \) given the currently fed target symbol and its current state vector. The decoder then computes a dot product between its state vector \( h^\text{dec}_t \) and a learned embedding vector \( e^\text{out}_{y_t} \) for each possible output symbols in the vocabulary \( y_t \in Y \), and normalizes the resulting scores to get a distribution over all possible symbols:

\[
p(y_t | y_{<t}, z_1, ..., z_n) = \text{softmax} \left( E^\text{out} \cdot h^\text{dec}_t \right)
\]

where \( \text{softmax} \) is a function that takes a vector of scalars and normalizes it into a probability distribution. That is, each dot product \( E^\text{out} \cdot h^\text{dec}_t \) produces a scalar score for the output symbol \( y_t \), and these scores are normalized by exponentiation and division by their sum. This results in a probability distribution over the output symbols \( y = Y \) at time step \( t \).

3.2 Attention models

In attention-based models, in each step the decoder can leverage a different weighted average of all latent vectors \( z = (z_1, ..., z_n) \) [17, 38], and not only the last state of the encoder as in the traditional seq2seq models. The weight that each \( z_i \) gets in this weighted average can be thought of as the attention that this input symbol \( x_i \) is given at a certain time step. This weighted average is produced by computing a score for each \( z_i \) conditioned on the current decoder state \( h^\text{dec}_t \). These scores are normalized such that they sum to 1:

\[
\alpha_t = \text{softmax} \left( z \cdot W_a \cdot h^\text{dec}_t \right)
\]

That is, \( \alpha_t \) is a vector of positive numbers that sum to 1, where every element \( \alpha_{ti} \) in the vector is the normalized score for \( z_i \) at decoding step \( t \). \( W_a \) is a learned weights matrix that projects \( h^\text{dec}_t \) to the same size as each \( z_i \), such that dot product can be performed.

Each \( z_i \) is multiplied by its normalized score to produce \( c_t \), the context vector for decoding step \( t \):

\[
c_t = \sum_i^n \alpha_{ti} \cdot z_i
\]

That is, \( c_t \) is a weighted average of \( z = (z_1, ..., z_n) \), such that the weights are conditioned on the current decoding state vector \( h^\text{dec}_t \). The dynamic weights \( \alpha_t \) can be thought of as the attention that the model has given to each \( z_i \) at decoding step \( t \).

The context vector \( c_t \) and the decoding state \( h^\text{dec}_t \) are then combined to predict the next target token \( y_t \). A standard approach [38] is to concatenate \( c_t \) and \( h^\text{dec}_t \) and pass them through another learned linear layer to predict the next symbol. I.e., multiply the concatenated vector by another learned matrix \( W_e \):

\[
h^\text{dec}_t = W_e \left[ c_t; h^\text{dec}_t \right]
\]

The probability of the target sequence can be factorized as:

\[
p(y_t | y_{<t}, z_1, ..., z_n) = \text{softmax} \left( E^\text{out} \cdot h^\text{dec}_t \right)
\]

Note that target symbol prediction in non-attentive models (Equation (1)) is very similar to the prediction in attention models (Equation (2)), except that non-attentive models use the decoder’s state \( h^\text{dec}_t \) to predict the output symbol \( y_t \), while attention models use \( h^\text{dec}_t \) which is the decoder’s state.
kinds:
Given a binary procedure composed of basic blocks \( P = \{BB_1, BB_2, \ldots \} \) we construct \( P \)'s CFG, \( G_P \). A CFG is a directed graph comprised of nodes which correspond to \( P \)'s basic blocks (BBs), connected by edges according to control flow instructions, i.e., jumps between basic-blocks. For clarity, in the following we: (i) add an artificial entry node BB denoted \( \text{Entry} \), and connect it to the original entry BB and, (ii) connect all exit-nodes, in our case BBs ending with a return instruction (exiting the procedure), to another artificial sink node \( \text{Sink} \).

We wish to represent \( P \) using sequences of reconstructed call sites, such as the one shown in Figure 1(d). For every path \( p \) in \( P_G \), we use \( \text{instructions}(p) \) to denote the sequence of instructions as executed along \( p \). We use \([P]\) to denote the set of sequences of instructions along simple paths from \( \text{Entry} \) to \( \text{Sink} \), that is:

\[
[P] = \{ \text{instructions}(p) \mid p \in \text{simplePaths(Entry, Sink)} \}
\]

**Extracting call site sequences from instruction sequences**

For every instruction sequence, \( s \in [P] \), we extract a single call site sequence. This is performed in three steps (examples from Fig. 1):

- Scanning \( s \)'s instructions until we encounter a call, e.g., \( \text{call } \_\text{getaddrinfo} \).
- Reconstructing the call to include argument registers, e.g., \( \text{getaddrinfo(rdi, rsi, rdx, rcx)} \).
- Transform the call into a call site, e.g., \( \text{getaddrinfo(ARG, ARG, CONST, CONST)} \).

We refer the reader for the technical implementation details for the first two steps to Section 6, and focus on the last step of creating the call sites.

We transform every call argument register to a symbol marking the value stored in it. If the last instruction writing to the register assigned a concrete value to it, e.g., \( \text{mov rdx, 2} \) (Fig. 1(b), this concrete value, i.e., the number “2” is used. Otherwise, it is transformed into one of four argument “kinds”:

-ARG: result of a calculation or a direct use of one of \( P \)'s arguments.
-VAL: a return value from another called procedure called during the instruction sequence \( s \).
-GLOBAL: usage of a global value, offset or pointer, located in one of the data sections of the Executable and Linkable Format (ELF), including BSS.
-CONST: a constant expression containing some computation over values local to the procedure such as a calculation of a pointer value to the procedure’s stack frame. For example, \( \text{rdx} \) and \( \text{rcx} \) in \( \text{getaddrinfo} \) in Fig. 1(b).

Using Pointer-Aware Slicing to Determine Kinds

To determine the kind of every call-site register used as callee argument, we require a way to examine all instructions involved in creating its value at the call-site location. These operations are usually performed by calculating a program slice \([57]\) and analyzing it. In our case, we require a pointer-aware static-program slice. For this we adapt the definition of Lyle and Binkley \([39]\) to be used for assembly instructions. For each program location \( i \), in our case the \( i \)'th instruction in a sequence \( s \in [P] \), we define the following slice information sets:

\[
\begin{align*}
&\text{defs}(i) = \text{a set of all registers written to in } i. \\
&\text{refs}(i) = \text{a set of all registers read from in } i. \\
&\text{Idefs}(i) = \text{a set of all memory addresses written to in } i. \\
&\text{Irefs}(i) = \text{a set of all memory addresses read from in } i.
\end{align*}
\]

Fig. 2 shows an example of slice information generation for two instructions. In line (1), we see that the addition result is stored in \( \text{rax} \), while \( \text{rax} \) and \( \text{rbx} \) are read from. In this instruction the memory is not read or written. In line (2) we see that both \( \text{rax} \) and \( \text{rbx} \) are read to generate the read and write addresses. We use quotation marks to emphasize that the full memory offset expression, “\( \text{rbx+5} \)”, is used when reading from memory, and that value is written into the memory at offset “\( \text{rax+rbx} \)”.

We define the rules for generating the slice information sets for each instruction according to the Intel x64 spec. By examining the slice created for each register-argument in every call site we deduce a suitable kind for each one. We defer the reader to Section 6 for more details on how the classification to kinds is performed.

Following the process of applying these three steps to every instruction-sequence \( s \in [P] \), we extract \( [P] \) call site
sequences, which serve as our representation of \( P \). This representation is used in our training and prediction processes which are described in the next section.

5 Model

In this section we describe our neural model that encodes call site sequences (Section 4) and decodes a likely name.

5.1 Motivation

A key observation in this work is the understanding that focusing on call sites is useful for predicting procedure names. As we show in Table 3, simply encoding the sequence of call sites as they appear in the binary produces useful predictions in some cases, and achieves an F1 score of 42.25. However, there are cases in which the order of the calls as they appear in the binary prevents the model from predicting the correct name.

Such an example is the procedure from Figure 1. Simply looking at the sequence of call instructions results in the following sequence:

```
call memset
call getaddrinfo
call gai_strerror
```

This example demonstrates that using the textual order of call instructions as they appear in the binary makes it very difficult to understand the procedure: calls to `close`, `strerror` and `errno_location` are interleaved with the successful path of calls: `memset` → `getaddrinfo` → `socket` → `setsockopt` → `bind` → `listen`. In contrast, using our architecture results in predicting the less informative name `tssockfd`. Indeed, while the true name of this procedure is `tssockf`, creating multiple, short and coherent CFG sequences (Figure 4) using our architecture results in predicting the name `create_server_socket`; encoding the textual call sequence (Figure 3) results in predicting the less informative name `tssock_getfd`.

5.2 High-level view

Our model follows the general encoder-decoder architecture [23, 56] with attention [17, 38] for sequence-to-sequence (seq2seq) models, with the significant difference that the input is not a standard single sequence of symbols, but a set of call site sequences. On a high-level, the key idea is to represent a binary procedure as a set of its call site sequences, each composed of call sites (as described in Section 4). Our basic building blocks are embeddings, i.e., vectors for procedure name subtokens (e.g., vectors for each of `open` and `file` in `open_file`) and argument kinds (e.g., ARG and CONST). These embeddings are initialized randomly, and their values are learned. We learn to represent each call site as a composition of these vectors. We learn a call site sequence as a sequence of call site vectors; finally, we predict (“decode”) the target procedure name word-by-word while considering a dynamic weighted average of call site vectors at each step. That is, the call site vectors are trained to capture the semantic information in the call site, and the amount of attention their call site sequence should get conditioned on the previously predicted word.

The neural network is trained end-to-end by optimizing the cross-entropy loss [50, 51] of the target sequence.

5.3 Encoder

In our model, we employ a similar architecture to the standard attention seq2seq (Section 3), with the following significant differences:

1. The input representations \( z \) are not simple word vectors, but aggregations of call site sequences.
2. The sequence that the encoder learns is the sequence of call sites.
3. Instead of a single sequence of input vectors, we compute a set of call site sequences and our decoder attends to their representations.

We define a vocabulary of learned embeddings \( E^{\text{names}} \). This vocabulary assigns a vector for every subtoken of API name which was observed at the training corpus. For example, if the training corpus contains a call to `open_file`, each of `open` and `file` is assigned a vector in \( E^{\text{names}} \). These vectors are initialized randomly and learned simultaneously with the rest of the network.

Additionally, we define a learned embedding vector for each argument kind, e.g., ARG, VAL, CONST or GLOBAL (Section 4), and for every actual value (e.g., the number “1”) that occurred in training data at least 3 times. We denote
Neural Reverse Engineering of Stripped Binaries

![Diagram](image)

**Figure 5.** Our model encodes each call site as the subtokens in the called API and the kinds of passed arguments; an LSTM encodes sequences of callsites; finally, the decoder uses all of the encoded sequences to generate the output sequence.

the matrix containing these vectors as $E^{kinds}$. We represent a call site by summing the embeddings of its API subtokens, and concatenating with up to $k_{kinds}$ of argument kind embeddings:

$$
encode_{callsite}(w_1, w_{k_{subtokens}}, Kind_1, ..., Kind_{k_{kinds}}) = 
\left[ \left( \sum_{i=1}^{k_{subtokens}} E^{names}_{w_i} \right) ; E^{kinds}_{1} ; ... ; E^{kinds}_{k_{kinds}} \right]
$$

For example, the call site `open_file(ARG, CONST)` with $k_{kinds} = 2$, results in the vector:

$$
z = \left[ \left( E^{names}_{open} + E^{names}_{file} \right) ; E^{kinds}_{ARG} ; E^{kinds}_{CONST} \right].
$$

If $k_{kinds}$ is greater than the number of arguments, we simply pad the remaining kind slots with an embeddings for an additional “no-argument” symbol. In our experiments, we used up to 10 arguments, i.e., $k_{kinds} = 10$. Next, we learn a call site sequence using a bidirectional LSTM - we train two LSTMs that learn the sequence from its beginning to its end, and vice-versa:

$$h^{-}_1, h^{+}_1 = LSTM \left( callsite_1, ..., callsite_{kseq} \right)$$

$$h^{-}_1, h^{+}_1 = LSTM \left( callsite_{kseq}, ..., callsite_1 \right)$$

Where $k_{seq}$ is the maximal length of a call site sequence. In our experiments, we used $k_{seq} = 60$. We next represent each call site sequence by concatenating the last state vectors of forward and backward LSTMs:

$$z = \left[ h^{-}_{kseq}, h^{+}_{kseq} \right]$$

Finally, given a program which is represented as a set of call site sequences, we represent the entire program as a set of its call site sequence encodings: $\{z_1, z_2, ..., z_n\}$

**Decoder Initial state** To provide the decoder with an initial state, we simply average the call site sequence vector encodings:

$$h^0_{dec} = \frac{1}{n} \sum_{i=1}^{n} z_i$$

**Design decisions** This architecture is tailored to model our call site sequence analysis: each API name is represented as a sum of its subtokens - this loses the order of the words and represents the name as a set of its subtokens (e.g., `open_file` is represented equally to `file_open`); constant arguments keep their value while variable arguments keep their origin; the API name is concatenated with its argument vectors - which is a lossless composition; a sequence of encoded callsites is aggregated using an LSTM which is a useful technique to model sequences; and finally, the decoder’s initial state is computed as an average of encoded sequences – this represents the entire procedure as a set of its encoded call site sequences (i.e., there is no order between the multiple sequences in a procedure).

Figure 5 portrays our model’s architecture: subtoken embeddings of API calls are summed (e.g., the vectors of `open` and `file` in `open_file`) and concatenated with the vectors of the kinds of the arguments to construct an encoded call site; a (bidirectional) LSTM reads the encoded call sites one-by-one; the final states of all encoded sequences are averaged to initialize the decoder LSTM; and finally, the decoder LSTM decodes the target procedure name word-by-word while attending over the encoded call site sequences.

**5.4 Decoder**

Our decoder operates much like decoders of contemporary seq2seq attention models (Section 3.2). Given a set of encoded call site sequences $z = \{z_1, ..., z_n\}$, the decoder predicts the next output symbol, i.e., procedure name subtoken, while attending over $z$. At training time, each true target symbol $y_{t-1}$ is fed to the decoder in turn to compute a distribution for $y_t$ over the possible target symbols $Y$. At test time, when the true $y_{t-1}$ is unknown, the decoder reads the previously-predicted symbol $\hat{y}_{t-1}$ instead, and chooses $y_t$ greedily as the target symbol that was assigned with the highest probability.
The decoder attends over the encoded call site sequences similarly to the way that a seq2seq model attends to the input states. By attending over the call site sequences z, the decoder is able to select the relevant call site sequences during each decoding step.

5.5 Training
To train the network we optimize the cross-entropy loss \( H(p_t, q_t) = \sum_{t=0}^{m} \left( \sum_{y \in Y} p_t(y) \log q_t(y) \right) = -\sum_{t=0}^{m} \log q_t(y_t) \)

That is, minimizing the cross-entropy loss is equivalent to maximizing the log-likelihood that the model assigns to the training data.

6 Implementation
6.1 Reconstructing Call Site Representations
Handling Imported Procedures We focus our approach and explanation on Linux Intel 64-bit executables. Linux executables usually import external procedures at load time, and declare these as dependencies in a special section in the ELF header. This includes LIBC, which provides the API for most OS related functionality (e.g., opening a file using `open()`).

Our analysis leverages comprehensive information from these imported procedures, including: (i) addresses in the loaded executable, and (ii) the number of arguments and their type.

To gather addresses in the loaded executable (i), we must analyze the ELF and construct the full list of aliases for every external procedure used. This includes parsing the PLT (Procedure Linkage Table) which is used by the executable procedures to call external procedures, and the Global Offset Table (GOT) containing the addresses in use (for a brief summary about how GOT and PLT are used to implement position independent code, see [7]).

To extract the number of arguments and their types (iii) we use the lists of debug symbols for the imported libraries. These symbols are represented in the DWARF format [2].

Using all this information, we reconstruct the prototype of every imported procedure used by the executable according to the Application Binary Interface (ABI) [6], which dictates the calling convention. In our case System-V-AMD64-ABI the first six procedure arguments which fit in the native 64-bit registers are passed in the following order: rdi, rsi, rdx, rcx, r8, r9. Return values which fit in the native register are returned using rax. We direct the reader to the ABI for further details on how floats and bigger arguments are handled. For example, libc’s `open()` is defined by the following C prototype: `int open(const char *pathname, int flags, mode_t mode)`. As all arguments are pointers or integers they can be passed using native registers, and our reconstruction process results in the following binary prototype: `rax = open(rdi, rsi, rdx)`.

An example of performing this process was shown in Fig. 1.

Algorithm 1: LookForKinds

```plaintext
Input: value – the value searched for, i – instruction index
Output: Kinds – the kinds gathered from the slice
Kinds ← \emptyset
1 if i == −1 then
2 Kinds ← Kinds \cup ARG
3 else
4 allDefs ← def_{f_1}(i) \cup \text{idef}_{f_2}(i)
5 if value ∈ (allDefs) then
6 if isCallInstruction(i) then
7 Kinds ← Kinds \cup VAL
8 else
9 for ref ∈ (\text{ref}_{f_1}(i) \cup \text{iref}_{f_2}(i)) do
10 if isConstExpr(ref) then
11 /* Adds CONST or GLOBAL */ */
12 Kinds ← Kinds \cup ConstKind (ref)
13 else
14 Kinds ← Kinds \cup LookForKinds(ref, i−1)
```

Slice Computation in The Context of a Sequence
Alg. 1 details the process of translating program slices for argument registers to argument kinds, mentioned in Section 4. We note that \( def_{f_1}(i), \text{idef}_{f_2}(i) \) etc’ are defined in the context of \( s \in P \), which is \( P \)’s instruction-sequences set.

Alg. 1 accepts as input a value \( value \) which can be a register or memory offset, and an instruction index to start from \( i \). Alg. 1 gathers the different kinds of values used to generate \( value \), records and returns them using \( Kinds \). Alg. 1 works by walking backwards in \( s \) and looking for the first instruction which defines \( value \), or in our case – writes into it. This is done by checking our slicing instruction sets \( def_{f_1} \) and \( idef_{f_2} \). This writing instruction can be a call site, in such case we mark this fact by adding VAL to \( Kinds \). (because VAL represents return values from another called procedures). In any other case, we examine all of the values referenced in \( i, \text{ref}_{f_1}(i) \cup \text{iref}_{f_2}(i) \). We detect CONST and GLOBAL values using \text{ConstKind}, updating \( Kinds \) accordingly. \text{ConstKind} detects globals by comparing the value used against the location of ELF sections containing globally accessible data, e.g., .data and .rodata (in these sections the compiler places global variables and constants respectively). When the value is not a global it is marked CONST. Then, we recursively look

Yaniv David, Uri Alon, and Eran Yahav
for all the instructions that write to the registers referenced and all memory offsets dereferenced throughout this instruction. If during our search we finished scanning the whole sequence, identified by reaching the $-\text{l}$ index, we recognize that this value uses one of $P$’s arguments, again marking this in $\text{Kinds}$.

By calling Alg. 1 for every register argument in every call site in $s$ we get a set of all the kinds of values used as arguments. Next, we select the representative kind by the following priority order: (1) $\text{VAL}$, (2) $\text{ARG}$, (3) $\text{GLOBAL}$, (4) $\text{CONST}$. For example, if Alg. 1 returned the set $\{\text{VAL}, \text{ARG}\}$ the final selected kind for this register argument will be $\text{VAL}$. This hierarchy represents the certainty level we have regarding this value: whether the value was created by another procedure we know nothing about it, was created using one of $P$’s argument we know something about it, gradually reaching the point in which we know the specific value used as an argument, where we use it instead of an argument kind.

We note that to provide intuition, Figure 1 shows argument kinds calculated in the context of the entire CFG. This is actually not possible, as using different sequences might result in different kinds for the same argument register.

7 Evaluation

We implemented our approach in a tool called Nero. We evaluate our approach using Nero to predict procedure names in real stripped binary executables. This section is thus composed of (i) a description of our experiment setup (Sec. 7.1), (ii) our main experiment, in which we show and discuss Nero’s performance for predicting procedure names (Sec. 7.2), (iii) an ablation study of the importance of the different components of our system to its overall performance (Sec. 3), (iv) details regarding a comparison between Nero and De-bin, a recent work performing debug symbols prediction for stripped binaries (Sec. 7.4), and (v) an in-depth analysis of our prediction results (Sec. 7.5).

7.1 Experimental Setup

Building a Corpus of Executables To create a suitable dataset to test our approach in predicting procedure names, we wanted it to be as diversified as possible: spanning across different application types, e.g., networking, games, graphics libraries, and built by commercial companies, open-source groups and independent developers.

To achieve this goal we built our corpus from a mixed collection of: (i) packages stored as a part of the Ubuntu 16.4 software repositories; (ii) public GitHub [3] repositories; and (iii) software packages found by crawling the web looking for Linux open-source software (e.g., the GNU [4] website). We limited our dataset to executables with debug information or executables we compiled ourselves, structuring our dataset as a list of executables alongside a list of (procedure location, procedure name) pairs in each executable.

We removed all executables compiled from C++ code and libraries used for creating Python packages, as these employ very different naming schemes for procedures.

Corpus statistics Following our crawling efforts and preprocessing stage, our corpus contains ~12,000 executables, containing ~60,000 procedures. The vocabulary for all API subtokens contains 6242 tokens, the vocabulary for target names (procedure predicted names) contains 3984 tokens, and the vocabulary for constant values used as procedure call arguments contained 2095 numbers.

Training We trained our neural model using a Tesla V100 GPU. For training our model we used 80% of our corpus data, leaving 10% for validation and 10% for our final test run. We took target subtokens and API subtokens that occurred at least 3 times in the training data; we used embeddings of size 128 for target subtokens and API subtokens; to encode call site sequences we use bidirectional LSTMs with 128 units each; the decoder LSTM had 512 units. We used dropout [55] of 0.25 on the API embeddings and the LSTMs. We use the Adam [34] optimization algorithm, an adaptive gradient descent method commonly used to train neural networks. We trained our model for about 100 epochs, until the validation score stopped improving for 20 consecutive epochs (‘early stopping’); we tune hyperparameters on the validation set, and evaluated the final model on the test set. Using a Tesla V100 GPU, each epoch takes 8 minutes. Training the model to convergence takes about 14 hours.

Evaluation Metrics Following previous works [11, 14], we measure precision, recall and F1 score over procedure name subtokens, case insensitive and ignoring non-alphabetical characters. This is based on the assumption that for a true name of $\text{write}_\text{file}$: $\text{file}_\text{write}$ is equally helpful for a human reverse engineer; a prediction of $\text{write}$ is partially helpful; and a prediction of $\text{write_text}_\text{file}$ contains information (text) that is not necessarily correct.

Baseline We compare our model with BiLSTM text - in which we do not perform any program analysis, and instead apply a powerful seq2seq architecture of two bidirectional LSTMs as the encoder, two decoder layers and attention. In this configuration, learning was applied on the assembly code directly.

7.2 Results

Trainable models on different datasets Table 1 shows the results of our main experiment, comparing the performance of Nero with the direct approach of learning the assembly code using bidirectional LSTMs. To better showcase the main differences between the two, we performed the experiments across two datasets: in the first we only used executables from the GNU packages, e.g., wget and coreutils, and in the other we used our full dataset (including the GNU packages). Statistics of these two datasets are shown in Table 2.
As we can see from the results (Table 2), both tools achieve better results under the reduced GNU only dataset. This dataset is almost an order of magnitude smaller, yet examining the major differences in the size of target and API vocabulary (shown, for each dataset, in the second line of Table 2), joined with the way this dataset was selected, leads to the understanding that this dataset is more homogeneous w.r.t the types of applications, thus compelling the use of specific APIs and naming conventions. While normally trainable models thrive from more data, in this case both models perform better in this setting.

On our full dataset, Nero greatly outperforms the BiLSTM model by 50% relative. This is due to the inability of the BiLSTM to examine the calls in the order they are performed in the procedures run. Nero, on the other hand, is trained using the seq of call site sequences, allowing it to produce more accurate predictions.

### 7.3 Ablation study

| Model                  | Precision | Recall | F1  |
|------------------------|-----------|--------|-----|
| Nero                   | 55.48     | 51.31  | 53.31|
| Nero no-decode         | 33.57     | 33.58  | 33.57|
| Nero no-kinds          | 48.86     | 47.47  | 48.16|
| BiLSTM calls           | 39.53     | 45.38  | 42.25|
| BiLSTM call-sites      | 46.89     | 41.73  | 44.44|

Table 3. Variations on the model of Nero, ablatting components of our model and components of our analysis.

To evaluate the contribution of our call-site analysis, we compare our model with the following configurations:

1. **Nero no decode** - uses the same encoder as Nero, but follows He et al. [29] and predicts the target procedure name as a **monolithic symbol** rather than a sequence of subtokens. The comparison with this ablation aims to investigate the importance of **decoding** in the task of procedure name prediction.

2. **Nero no kinds** - to understand the importance of our analysis of argument **kinds**, in this configuration we ignored argument kinds. We use the same analysis and model architecture, except that call-sites are encoded using the name of invoked procedure only, without any information about the kind of arguments or their number.

3. **BiLSTM calls** - in which we use two layers of bi-directional LSTMs with attention to encode **only call instructions**, without other assembly instructions that might distract the encoder. This configuration performs a partial program analysis to determine the name of the invoked procedures, if they are available to our model as well.

4. **BiLSTM call-sites** - in which we encode call instructions with all the argument **kind** information. This configuration is similar to our settings, with the main difference that in this configuration the order of the call sites is **their order in the assembly code**: there is no analysis of jumps between basic blocks.

Table 3 Shows the performance of the different configurations. The BiLSTM models, not using the paths in the procedure’s CFG, trails 10% behind Nero and 6% behind Nero no-kinds. BiLSTM call-site is slightly out-performed by BiLSTM calls, even tough the former has more information encoded in the argument kinds. We suspect that this is the result of the model treating the whole call site as one unit, including the arguments, unlike Nero which embeds the target work separately from the argument kinds. Comparing Nero no-kinds to Nero shows that ignoring the information stored by the argument kinds causes a degradation of 5%. It is important to note that even though the extraction of argument kinds is **very lightweight** compared to the time it takes to train the model, its critical in improving its predictions. Removing the decoder and predicting the procedure name as a monolithic symbol degrades the F1 score by about 20 points. This shows the importance of a compositional prediction which exists in our decoder, and does not exist in the non-neural model of He et al. [29].

**Qualifying the Use of Kinds** Following our previous experiment, we wanted to examine the way the use of argument kinds affects the predictions between Nero and Nero no-kinds. We note that the full size of our test set is 5277 procedures. We report some interesting differences:

- The use of kinds helped the model to improve 148 predictions from a full false prediction to a full positive prediction.
- The other way around, only 8 procedures were successfully predicted by the model trained without kinds.
Interestingly, all these procedures had only one sub-token in their name.

- 412 procedures receiving a full false prediction were partly predicted using kinds, with varying amount of subtokens in their name (1 to 5).
- 232 procedures improved from a partial prediction to a full positive prediction by using kinds.

7.4 Comparison to Debin

Recently, He et al. [29] presented Debin, a non-neural model for predicting debug information in stripped binaries based on Conditional Random Fields (CRFs). Conceptually, our model is much more powerful because it is able to generate out-of-vocabulary (OoV) procedure names from subtokens, while their CRF can only predict already-seen procedure names. One example for an OoV prediction is shown in the next section. At the binary code side, since our model is neural, at test time it can utilize unseen call site sequences (as shown in Section 2), while their CRF can only use observed relationships (for a detailed discussion about the advantages of neural models over CRFs, see Section 5 of [14]). Furthermore, their representation performs a shallow translation from binary instruction to connections between symbols, while our representation is based on a deeper analysis to find values stored in registers used as arguments to imported procedures.

As neither their code nor dataset are publicly available, our best effort is to perform a qualitative comparison to their work. We randomly select examples from our test set and compare them with their online tool [1]. Table 4 presents the results of this manual evaluation. As shown, in 10 of 10 random examples, procedure names produced by our model are much more accurate and descriptive.

7.5 Analyzing the Model’s Predictions

Out-Of-Vocabulary (OoV) predictions We begin by taking a deep-dive into the prediction of the procedure “cattle_configuration_set_property” from the cattle package (an inspector for Brainfuck programs). The model successfully predicts this procedure name without having seen this exact composition in its training data. As we have no precise way to “debug” the trained model to gather information about the origins and important samples seen along the way to allow this prediction, we try to speculate by examining the vocabularies used and other successful predictions made by the model.

Examining our full target name vocabulary, we see “config_get_property” exists in another package, as well as “set_file_property” exists in a third package. We note that both of these procedures were later successfully predicted as a part of the validation set. A wider inspection of the vocabulary shows that there are 30 other procedures with the name “get_property” and “set_property” to “learn from”. Finally, taking a closer look at the call site sequences representing “cattle_configuration_set_property” uncovers APIs with the sub-tokens “copy” and “write”, similar to the ones found procedures with “set_property” in their name.

Understanding partial predictions Taking a closer look at partial predictions reveals some patterns, helping us study them and divide them into groups. Fig. 5 shows a few examples from each of the more interesting and common groups.

The first group, “Programmers VS English Language”, depicts prediction errors caused by the programmer’s naming habits or errors. In the first line we see one example of a relatively common practice for programmers, the use of shorthand. In this case “cfg” was used instead of “config”, which is itself a shorthand for “configuration”. We note that these words appear 49, 635 and 44 times respectively in our vocabulary of target subtokens, justifying the selection of “config” by the model. The next line shows a typo, the omission of the separator between the two words “serversocket”. In both cases the programmer’s naming mishap is corrected by the model.

The next group, “Verb Replacement”, shows how much information is captured by the verb in the procedure name. In the first example, “parse” is replaced with “get”, losing some information about the work performed in the procedure. In the last example, “recv” is replaced with “get” which are almost synonymous, yet the former (should be “receive”) hints to a use in conjunction with a stream.

The next group, “Data Structure Name Missing” shows cases in which the same data is labeled using different terms yet this structure is addressed, in terms of memory access, and processed, in terms of APIs used, the same way. In the first example, a puzzles app for ubuntu, the (memory) blocks are labeled as puzzle piece while the model “treats” them as a block. The same goes, in the next example for the parsing of an RPM package, which the model simply “sees” as a tar archive.

The last group, “Literal Name”, shows what happens when the procedure performs some high-level function, while the model’s prediction only provides a literal description of what happens in the procedure. The first line shows how the high-level concept of activating a usb device (in the case of libpcap to allow usb sniffing) is missed by the model and instead predicted as a literal operation of logging (the operation), adding (the record) and opening (the socket to the usb interface).

8 Related Work

Machine learning for source code Several works have investigated machine learning approaches for predicting names in high-level languages. Most of these works focused on variable names [15, 19, 46], method names [9, 11, 14] or general properties of code [45, 47]. Another interesting application is measuring the likelihood of existing names to detect naming bugs [43, 49]. Most works in this field used either syntax only [20, 44], semantic analysis [10] or both [46]. Leveraging syntax only may be useful in languages such as Java...
Table 4. In 10 out of 10 random examples, procedure names produced by Nero are more descriptive and accurate than Debin

| Package | True reference | Nero | Debin [29] |
|---------|----------------|------|------------|
| wget    | do_conversion  | convert | gw__tmp630_gnome_help... |
| wget    | path_search    | path_search | cdbus_call_async |
| putty   | columns_base_add | columns_forall | videosrc_port_FreeBuffer |
| putty   | open           | open   | s3open     |
| cups    | httpTLSStart   | http_tls_start | go         |
| agensgraph | ReceiveTarFile | get_tar_file | dserver_get |
| libsmi  | dumpSmi        | dump_smi | execute_move |
| libsmi  | getOidString_1 | get_oid_string | radius_evaluate_condition |
| ibus    | xim_destroy_ic | remove_ic | daemon_message_func |
| sudo    | command_matches_normal | command_matches_normal | audio_write |

Table 5. Examining interesting groups of partial predictions

and JavaScript that have a rich syntax, which is not available in our difficult scenario of RE of binaries. In contrast with syntactic-only works such as Alon et al. [13, 14], working with binaries requires a deeper semantic analysis in the spirit of Allamanis et al. [10], which recovers sufficient information for training the model using semantic analysis.

Brockschmidt et al. [21] and Fernandes et al. [27] further leveraged semantic analysis with Gated Graph Neural Networks, where edges in the graph were relations found using semantic analysis. Graph neural networks are not easily applicable in our scenario, as the main observation in our work is the focus on sequences of call sites, rather than a complex graph structure. A recent work [26] learns distributed representations of C functions based on the CFG. We also use use the CFG, but in the more difficult domain of stripped binaries rather than C code.

Static analysis frameworks for RE [33] shows a statistical approach to using behavioral information to infer subclass/superclass relations and fill out any missing structural information in stripped binaries. [35] uses static and dynamic analysis to recover high-level types, by solving constraints created by lifting and analyzing assembly instructions. [48] presented CodeSurfer, a binary executable framework built for analyzing x86 executables, focusing on detecting and manipulating variables in the assembly code.

Similarity in binary procedures [25, 42] both address the problem of using one procedure or executable to find others similar to it. The former uses statically extracted hashed “strands”, re-optimized to allow for a more effective search. The latter uses a combination of static and dynamic techniques to extract a representation suited for this search.

Recurrent neural networks (RNNs), and specifically long short-term Memory (LSTM) networks [30] and gated recurrent units (GRUs) [23] were shown to be highly effective for representing sequences, and have been widely used for a variety of tasks, such as machine translation [17, 38, 56], reading comprehension [36, 53], speech recognition [18, 22, 24] and more [16, 40]. Usually, RNNs are used to learn a sequence of words or characters in the input, or to generate a sequence of output words. In our work, we use bidirectional LSTMs to learn sequences of call sites and another LSTM to decode the target procedure name given the input sequences.

In [54], recurrent networks were used for identifying procedure boundaries inside a stripped binary, identifying what addresses in the binary correspond to procedure bodies.

9 Conclusion
We present a novel framework for predicting method names in stripped binaries. The framework is based on a combination of a new representation for procedures in binaries, extracted using static analysis, with a new encoder-decoder architecture tailored to leverage this representation.

We evaluated our framework over 60,000 stripped procedures from over 10,000 executables. We show that our model achieves F1 score of 80.9 in predicting procedure names within GNU packages, and F1 score of 53.3 in a diverse, cross-package, dataset. To the best of our knowledge, this is
Neural Reverse Engineering of Stripped Binaries

the first work to leverage deep learning for reverse engineering procedure names for RE.

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A Appendix

A.1 Example full signature for a Win32 API method

```c
BOOL AccessCheckByTypeResultListAndAuditAlarmByHandleA(
    LPCTSTR ObjectTypeList,
    LPDWORD Flags,
    AUDIT_EVENT_TYPE AuditType,
    PSID PrincipalSelfSid,
    LPCSTR ObjectName,
    LPCSTR ObjectTypeName,
    HANDLE ClientToken,
    PGENERIC_MAPPING GenericMapping,
    DWORD DesiredAccess,
    LPCSTR ObjectCreation,
    BOOL ObjectCreation,
    LPDWORD GrantedAccess,
    LPVOID HandleId,
    LPCSTR SubsystemName,
    HANDLE AuditStatusList,
    LPDWORD AccessStatusList,
    BOOL AccessCheckByTypeResultListAndAuditAlarmByHandleA,
);```