## Using Recurrent Neural Networks for Decompilation

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We want better decompilation.

### Approach:

We use a model based on recurrent neural networks to translate from binary machine code to source code.

## Decompilation is Translating Binary Code to Source Code

```
12
                          ()
                              00
                                  70
                                       33
             ()
                 d3
                                                ()()
                 00
                      00
                          09
                              00
                                   d3
                                       12
        00
             00
                                                00
                      00
             00
                 0.0
                          0.0
                                   0.0
                                       0.0
78
    33
        ()
                                                00
    12
       () ()
            0.0
```

• • •

## Decompilation is Translating Binary Code to Source Code

```
00 d3 12 00 00 70 33 00
             0.0
                00
                   09
                       00
                          d3
      ()
         ()
                                    ()
                00 00 00
             00
78 33
         00
      00
                                    00
d3 12 00 00
```

```
g_return_if_fail(screen_info != NULL);
```

# Source Code is More Useful to Humans than Binary

- Human-Readable
- More analysis tools available for source
- Decompilation does not always produce the most useful output
  - Can leave in compiler artifacts, such as:
    - GOTOs
    - Stack pushes for function calls
- Newer techniques rely on compiler details
  - Very specific to individual compilers/languages
- Existing tools are expensive and often unavailable

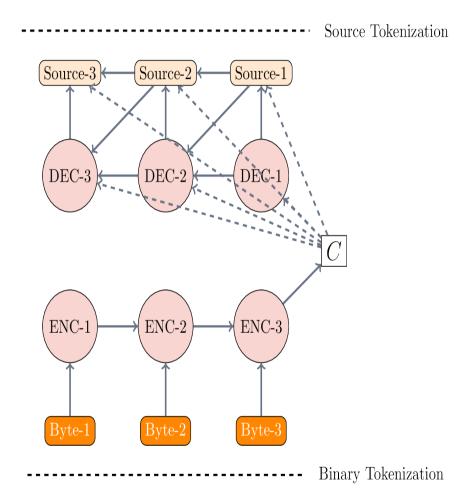
### Decompilation is a Translation Problem

- On some level decompilation is translating:
  - Machine-level binary code to higher-level source or intermediate code
- Look to the techniques for translating other equivalent sequences

### **Key insight:**

To we can translate from **binary** to **source** in the same way we can **translate natural languages**.

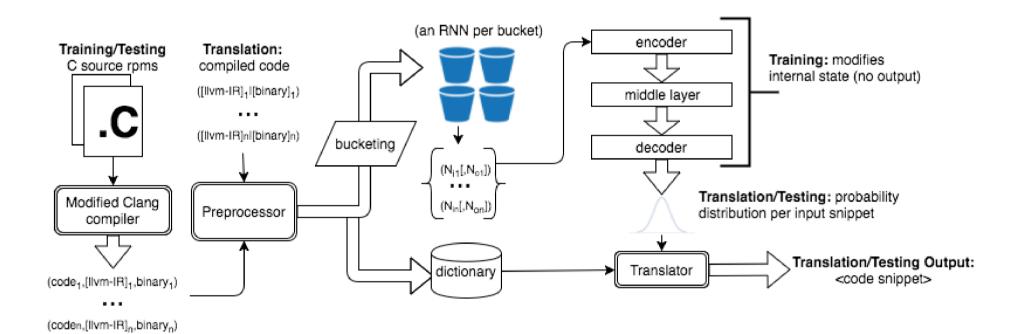
# What You Need to Know About Neural Networks (Not Much)



- Encoder-Decoder Model
  - Available off-the shelf with TensorFlow\*
  - Designed for translating sequences
- Adapt to translate compiled machine code to higher-level source
- Train model, then use for decompilation

<sup>\*</sup> https://www.tensorflow.org/

### Overview



### Creation of Parallel Corpuses

- Used a customized version of Clang to obtain a database of snippets of source code and the equivalent machine/binary code
  - Under certain compiler settings
- We obtained the corpus by compiling many open-source RPM packages
  - 1,151,013 paired snippets of source and binary

# The Encoder-Decoder Model Operates on Sequences of Integers

- We train the model on the paired snippets:
  - Machine code and the equivalent source code
  - Each snippet is represented as a sequence of integers

### For example:

Binary tokenization: 4 4 80 4 198 136 4 4 118 173 4 4 4 4 4 4 4 80 4 198 136 4 4 4 4 4 4 4 4 80 4 198 136 4 4

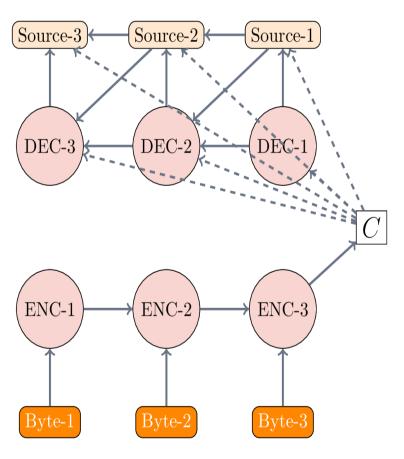
## Tokenize Binary and Source Into Useful Units

- Lex source into language-appropriate tokens
  - Keep most popular variable names
    - Normalize others
- Assign integers based on frequency in the corpus

Integer	Source Token	Integer	Source Token
4	(	15	}
5	)	16	*
6	;	17	if
7	,	18	var_3
8	var_0	19	0
9	function	20	"string"
10	=	21	]
11	var_1	22	[
12	->	23	var_4
13	var_2	24	
14	{	25	1

# Our Trained Model Takes Binary Machine Code as Input

----- Source Tokenization



### INPUT:

 00
 00
 09
 00
 d3
 12
 00
 00

 70
 33
 00
 00
 00
 00
 00
 00

 00
 00
 09
 00
 d3
 12
 00
 00

 78
 33
 00
 00
 00
 00
 00
 00
 00

 00
 00
 09
 00
 d3
 12
 00
 00

Binary Tokenization

## Our Trained Model Turns Binary Machine Code Into Tokens

Binary Tokenization

Source Tokenization Source-1 Source-2 Source-3 DEC-2 DEC-3 ENC-2 ENC-3 ENC-1 Byte-2 Byte-3

#### **Binary Tokenization:**

4 4 80 4 198 136 4 4 118 173 4 4 4 4 4 4 4 4 80 4 198 136 4 4 78 173 4 4 4 4 4 4 4 80 4 198 136 4 4



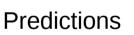
0.0 0.033 0.0 00 0.0 0.0 0.0d3 00 00 0.0 09 0.0 d3 12 0.0

## Our Trained Model Translates Binary Tokens to Source Tokens

Source Tokenization Source-3 Source-2 Source-1 DEC-2 DEC-3 ENC-2 ENC-ENC-3 Byte-3 Binary Tokenization

Source Tokenization:

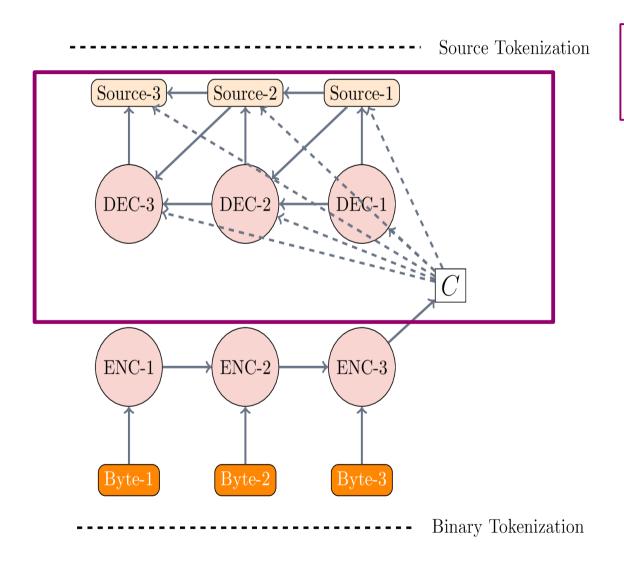
111 4 8 42 31 5 6



#### **Binary Tokenization:**

4 4 80 4 198 136 4 4 118 173 4 4 4 4 4 4 4 4 80 4 198 136 4 4 78 173 4 4 4 4 4 4 4 80 4 198 136 4 4

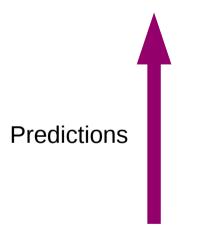
## Our Trained Model Translates Binary Tokens to Source Tokens



(Actual tokenizations are reversed to allow the model to build context)

Source Tokenization:

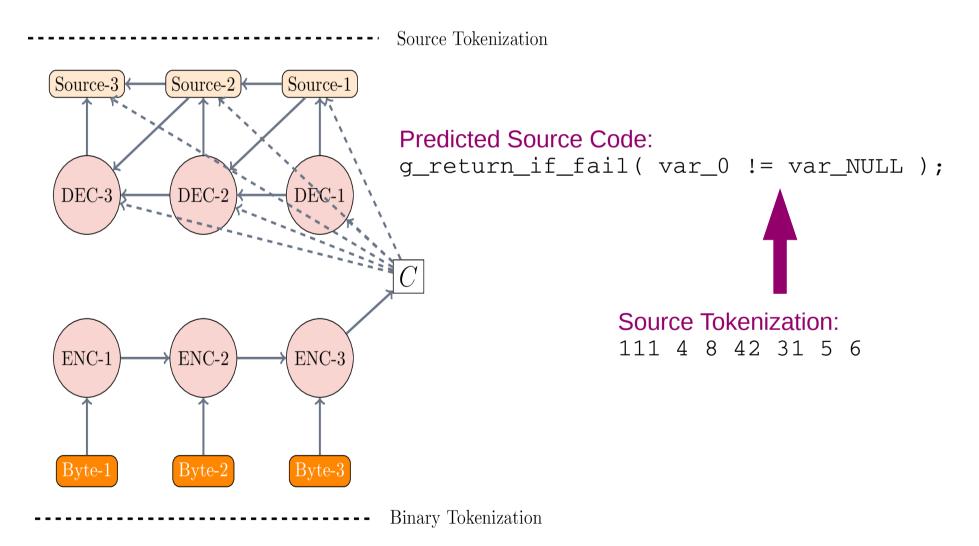
111 4 8 42 31 5 6



#### **Binary Tokenization:**

4 4 80 4 198 136 4 4 118 173 4 4 4 4 4 4 4 4 80 4 198 136 4 4 78 173 4 4 4 4 4 4 4 80 4 198 136 4 4

## Our Trained Model Turns Source Token Sequences Into Source Code



### Evaluating Accuracy and Usefulness

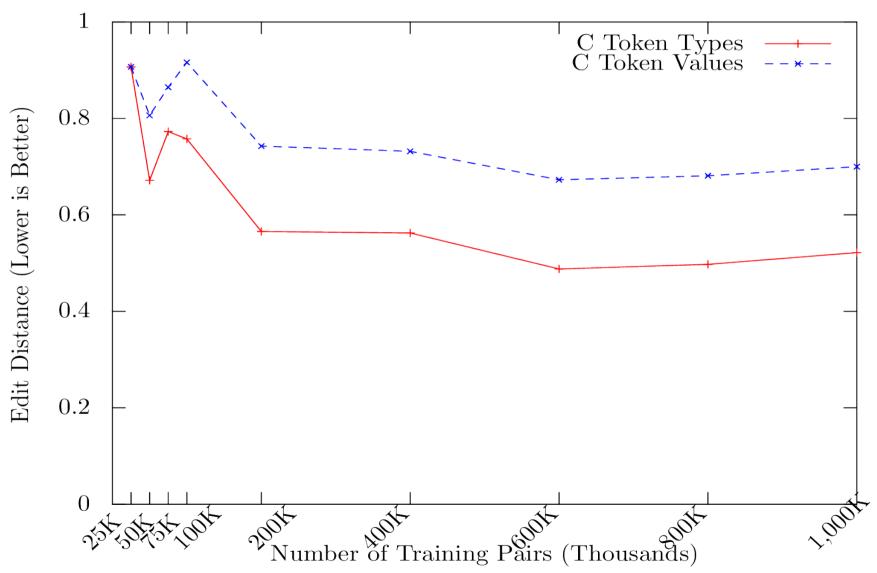
- We evaluate on a metric based on edit distance (lower is better)
  - Evaluation on recovery of exact token sequences
  - Evaluation on recovery of the correct types of tokens
- Ideally, we would like to do a user study to evaluate the usefulness of the translations

### **Research Questions:**

RQ1: How long do we have to train for useful translations?

RQ2: How effective is our technique at translating machine code binary to C source code?

# RQ1: The Effect of Additional Training Levels Out



### RQ2: Usefulness by Edit Distance

	Maximum Number of C Tokens Per Snippet	Mean Edit Distance	Mean Edit Distance on Token Types
All C Source		0.70	0.52
Small snippets	5	0.65	0.56
Small-medium	9	0.67	0.45
Medium	17	0.72	0.52
Large	88	0.75	0.55

# Example: Recovery of Function Call, Function Name, and Variable Name

Ground Truth:

```
g_return_if_fail(screen_info != NULL);
```

Translation:

```
g_return_if_fail( var_0 != var NULL );
```

# Example: Recovery of Function Call, Function Name, and Variable Name

Ground Truth:

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Translation:

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g_return_if_fail( var_0 != var_NULL );
```

# Example: Recovery of Function Call, Function Name, and Variable Name

Ground Truth:

```
g_return_if_fail(screen_info != NULL);
```

Translation:

```
g_return_if_fail( var_0 != var_NULL );
```

## Example: Recovery of the General Structure of a Statement

Ground Truth:

```
itr->e = h->table[i];
```

Translation:

```
var_0 - var_1 = var_2 - var_3;
```

- Edit distance: 0.64
  - Misses variable names and array index

# Example: Recovery of an if statement

• Ground Truth:

```
if (ts) {
    adjusted_timespec[0] = timespec[0];
    adjusted_timespec[1] = timespec[1];
    adjustment_needed = validate_timespec(ts);
}
```

• Translation:

```
if ( var_0 ) {
    function( var_1 , var_0->var_2 );
}
```

### Example: Recovery of a for loop

• Ground Truth:

```
for (node = tree->head; node; node = next) {
    next = node->next;
    avl_free_node(tree, node);
}
```

Translation:

```
for ( var_0 = var_1 ) var_0 != var_NULL ; var_0 =
    var_0->var_2 {
    function(var_0->var_3);}
```

### Technique Advantages

- Language-independence
- Recovers semantic knowledge about programs

### Summary

