

# Learning to Generate Corrective Patches using Neural Machine Translation

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**Abstract**—Bug fixing is generally a manually-intensive task. However, recent work has proposed the idea of automated program repair, which aims to repair (at least a subset of) bugs in different ways such as code mutation, etc. Following in the same line of work as automated bug repair, in this paper we aim to leverage past fixes to propose fixes of current/future bugs. Specifically, we propose Ratchet, a corrective patch generation system using neural machine translation. By learning corresponding pre-correction and post-correction code in past fixes with a neural sequence-to-sequence model, Ratchet is able to generate a fix code for a given bug-prone code query. We perform an empirical study with five open source projects, namely Ambari, Camel, Hadoop, Jetty and Wicket, to evaluate the effectiveness of Ratchet. Our findings show that Ratchet can generate syntactically valid statements 98.7% of the time, and achieve an F1-measure between 0.41-0.83 with respect to the actual fixes adopted in the code base. In addition, we perform a qualitative validation using 20 participants to see whether the generated statements can be helpful in correcting bugs. Our survey showed that Ratchet’s output was considered to be helpful in fixing the bugs on many occasions, even if fix was not 100% correct.

**Index Terms**—patch generation, corrective patches, neural machine translation, change reuse.



## 1 INTRODUCTION

Most software bug fixing tasks are manual and tedious. Recently, a number of techniques related to automated program repair have been proposed to help automate and reduce the burden of some of these tasks [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26]. These systems are also seeing practical use. For example, Facebook has announced that they started applying a system of automated program repair called SapFix in their large-scale products [27].

However, there are limitations in current approaches to automated program repair. First, there is a risk of overfitting to the training set (and breaking under tested functionality) in patch generation, especially generated tests tends to lead overfitting compared to human-generated, requirements-based test suites [28]. Second, correct patches may not exist in the search space, or correct patches cannot be generated because the search space is huge [29], [30]. Several studies address this search space issue by making use of existing human-written patches [31], [32], [33], [34], [35], [36], [37], [38], but those generated patches need to be validated with test suites. Therefore, investigating techniques that assist in the generation of patches without the need for tests, etc. are needed. Instead of exploring fix ingredients in the search space (search-based), we study the possibility of learning fix ingredients from past fixes (learning-based).

Recently, Neural Machine Translation (NMT) has been proposed and showed promising results in various areas including not only translation between natural languages (such as English and Japanese), but also other NLP tasks such as speech recognition [39], natural language parsing [40], and text summarization [41]. Similar techniques have been applied to code-related tasks [42], [43], [44], [45], [46], [47], [48]. The notable success of NMT in such a wide variety of tasks can be attributed to several traits: (1) It is an end-to-end machine learning framework that can be learned effectively from large data – if we have a large enough data source it is able to learn even complicated tasks such as translation in an effective way. (2) Unlike previous models for translation such as phrase-based translation [49] (which has also been used in code-related tasks such as language porting [50]), NMT is able to take a holistic look at the entire input and make global decisions about which words or tokens to output. In particular, for bug fixing we posit this holistic view of the entire hunk of code we attempt to fix is important, and thus focus on approaches using NMT in this work.

Hence, in this paper, we propose Ratchet, a NMT-based technique that generates bug fixes based on prior bug-and-fix examples. To evaluate the effectiveness of the technique, we perform an empirical study with five large software projects, namely Ambari, Camel, Hadoop, Jetty and Wicket. We use the previous Plastic Surgery approach, proposed by Barr *et al.* [51], as a comparison baseline and examine the effectiveness of our NMT-based technique. In particular, we quantify the number of cases where our NMT-based technique is able to generate a valid fix and how accurate the generated fixes are. Our findings showed that Ratchet is able to generate a valid statements in 98.7% of the cases and achieves an F1 measure between 0.41 - 0.83 with respect to the actual fixes adopted in the code base. For all five projects,

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Ratchet was able to either outperform or perform as well as the Plastic Surgery approach.

In addition to the quantitative validation, we also performed a survey with 20 participants to see whether the generated statements can help in correcting a bug (even if they were not 100% identical to the fix). Our findings show that survey participants find that the fixes generated by Ratchet are very helpful, even if they were not fully correct (although the correct fixes were most helpful).

The rest of the paper is organized as follows. Section 2 presents relevant terminology. Section 3 provides background about NMT. Section 4 details our approach. Section 5 sets up our experiments, discussing their design and the data used. Section 6 presents our results and Section 7 discusses the generality and some challenges facing NMT-based solutions. Related work is presented and contrasted in Section 8 and Section 9 concludes the paper.

Listing 1. An example of a change hunk in bug fixing.

```
Commit: 44074f6ae03031ab046b1886790fc31e66e2d74e
Author: Willem Ning Jiang
Date: Sat Jun 9 09:24:15 2012 +0000
Message: CAMEL-5348 fix the issue of Uptime
```

```
uptime /= 24;
long days = (long) uptime;
- long hours = (long) ((uptime - days) * 60);
+ long hours = (long) ((uptime - days) * 24);
String s = fmtI.format(days)
      + (days > 1 ? " days" : " day");
```

## 2 TERMINOLOGY

We use the term, *change hunk*, similar to the previous study by Ray et al. [52]. A *change hunk* is a list of program statements deleted and added contiguously. In a single commit to a code repository, typically there are multiple change regions in multiple files. Even in a single file, there can be multiple change regions. Those changed regions can be identified with *diff*. Although the previous study by Ray et al. included unchanged statements in a change hunk [52], we do not include them. We call deleted and added statements *pre-correction* and *post-correction* statements respectively. In Listing 1, the red statement is a pre-correction statement and the green statement is a corresponding post-correction statement, and these associated two statements are considered to be a change hunk.

In this study, we are interested in learning transforming patterns between corresponding pre-correction and post-correction statements. Thus, we ignore change hunks that only contain deleted or added statements. All change hunks studied in this paper are pairs of pre-correction and post-correction statements.

## 3 BACKGROUND

Neural machine translation, also called neural sequence-to-sequence models [53], [54], [55] is a method for converting one input sequence  $x$  into another output sequence  $y$  using neural networks. As the name suggests, the method was first conceived for and tested on machine translation; for converting one natural language (e.g. English) into another (e.g. French). However, because these methods can work

on essentially any problem of converting one sequence into another, they have also been applied to a wide variety of other tasks such as speech recognition [39], natural language parsing [40], and text summarization [41]. They have also seen applications to software for generation of natural language comments from code [42], generation of code from natural language [43], [44], [45], generation of API sequences [46], and suggesting fixes to learner code in programming MOOCs [47], [48].

In this section we briefly overview neural networks, then explain neural machine translation in detail.

### 3.1 Neural Networks

Neural networks [56], put simply, are a complicated function that is composed of simpler component parts that each have parameters that control their behavior. One common example of such a function is the simple multi-layer calculation below, which converts an input vector  $x$  into an output vector  $y$ :

$$\begin{aligned} \mathbf{h} &= \tanh(W_1 \mathbf{x} + b_1) \\ \mathbf{y} &= W_2 \mathbf{h} + b_2. \end{aligned} \quad (1)$$

Here,  $W_1$  and  $W_2$  are parameter matrices, and  $b_1$  and  $b_2$  are parameter vectors (called *bias* vectors). Importantly, the vector  $\mathbf{h}$  is a *hidden* layer of the neural network, which results from multiplying  $W_1$ , adding  $b_1$ , then taking the hyperbolic tangent with respect to the input. This hidden layer plays an essential role in neural networks, as it allows the network to automatically discover features of the input that may be useful in predicting  $\mathbf{y}$ .<sup>1</sup>

Because neural networks have parameters ( $W_1$ ,  $b_1$ , etc.) that specify their behavior, it is necessary to learn these parameters from training data. In general, we do so by calculating how well we do in predicting the correct answer  $\mathbf{y}'$  provided by the training data, and modify the parameters to increase our prediction accuracy. Formally, we do so by calculating a *loss function*  $\ell(\mathbf{y}, \mathbf{y}')$  which will (generally) be 0 if we predict perfectly, and higher if we're not doing a good job at prediction. We then take the derivative of this loss function with respect to the parameters, e.g.  $\frac{\partial \ell(\mathbf{y}, \mathbf{y}')}{\partial W_1}$ , and move the parameters in the direction to reduce the loss function, e.g.

$$W_1 \leftarrow W_1 - \alpha \frac{\partial \ell(\mathbf{y}, \mathbf{y}')}{\partial W_1}, \quad (2)$$

where  $\alpha$  is a learning rate that controls how big of a step we take after every update.

The main difficulty here is that we must calculate derivatives  $\frac{\partial \ell(\mathbf{y}, \mathbf{y}')}{\partial W_1}$ . Even for a relatively simple function such as the one in (1), calculating the derivative by hand can be cumbersome. Fortunately, this problem can be solved through a process of *back-propagation* (or *auto-differentiation*), which calculates the derivative of the whole complicated function by successively calculating derivatives of the smaller functions and multiplying them together using the chain rule [58]. Thus, it becomes possible to train arbitrarily complicated

1. In fact, by adding this hidden layer, a simple function such as the above is able to accurately perform any prediction task given a large enough  $\mathbf{h}$  and enough training data, and thus neural networks are known as *universal function approximators* [57].

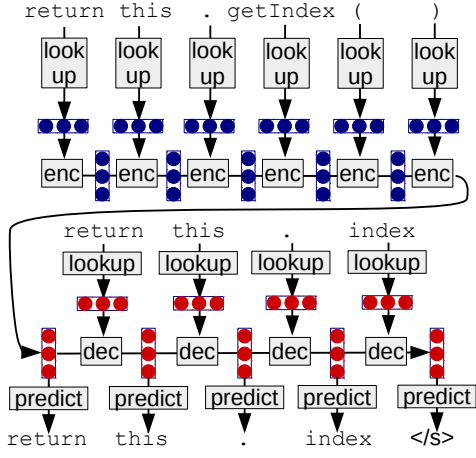


Fig. 1. An example of neural MT encoder-decoder framework used in translation.

functions, as long as they are composed of simple component parts that can be differentiated, and a number of software libraries such as TensorFlow [59] and DyNet [60] make it possible to easily do so within applications.

### 3.2 Neural Machine Translation

Neural machine translation is an example of applying a complicated function learnable by neural nets and using it to solve a complicated problem: translation. To generate an output  $\mathbf{y}$  (e.g. corrected hunk of code) given an input  $\mathbf{x}$ , these models incrementally generate each token in the output  $y_1, y_2, \dots, y_{|\mathbf{y}|}$  one at a time. For example, if our output is “return this . index”, the model would first predict and generate “return”, then “this”, then “.”, etc. This is done in a probabilistic way by calculating the probability of the first token of the output given the input  $P(y_1 | \mathbf{x})$ , outputting the token in the vocabulary that maximizes this probability, then calculating the probability of the second token given the first token and the snippet  $P(y_2 | \mathbf{x}, y_1)$  and similarly outputting the word with the highest probability, etc. When training the model, we already know a particular output  $\mathbf{y}$  and want to calculate its probability given a particular snippet  $\mathbf{x}$  so we can update the parameters based on the derivatives of this probability. To do so, we simply multiply these probabilities together using the chain rule as follows:

$$P(\mathbf{y} | \mathbf{x}) = P(y_1 | \mathbf{x})P(y_2 | \mathbf{x}, y_1)P(y_3 | \mathbf{x}, y_1, y_2) \dots \quad (3)$$

So how do neural MT models calculate this probability? We will explain a basic outline of a basic model called the *encoder-decoder model* [54], and refer readers to references for details [54], [55], [61]. The encoder-decoder model, as shown in Figure 1 works in two stages: first it *encodes* the input (in this case  $\mathbf{x}$ ) into a *hidden vector* of continuous numbers  $\mathbf{h}_x$  using an encoding function

$$\mathbf{h}_{x,|\mathbf{x}|} = \text{encode}(\mathbf{x}). \quad (4)$$

This function generally works in two steps: looking up a vector of numbers representing each token (often called “word embeddings” or “word vectors”), then incrementally adding information about these embeddings one token at a

time using a particular variety of network called a *recurrent neural network* (RNN). To take the specific example shown in the figure, at the first time step, we would look up an embedding vector for the first token “return”,  $e_1 = e_{\text{return}}$  and then perform a calculation such as the one below to calculate the hidden vector for the first time step:

$$\mathbf{h}_{x,1} = \tanh(W_{\text{enc},e}e_1 + b_{\text{enc}}), \quad (5)$$

where  $W_{\text{enc},e}$  and  $b_{\text{enc}}$  are a matrix and vector that are parameters of the model, and  $\tanh(\cdot)$  is the hyperbolic tangent function used to “squish” the values to be between -1 and 1.<sup>2</sup> In the next time step, we would do the same for the symbol “.”, using its embedding  $e_2 = e_{\cdot}$ , and in the calculation from the second step onward we also use the result of the previous calculation (in this case  $\mathbf{h}_{x,2}$ ):

$$\mathbf{h}_{x,1} = \tanh(W_{\text{enc},h}\mathbf{h}_{x,1} + W_{\text{enc},e}e_2 + b_{\text{enc}}). \quad (6)$$

By using the hidden vector from the previous time step, the RNN is able to “remember” features of the previously occurring tokens within this vector, and by repeating this process until the end of the input sequence, it (theoretically) has the ability to remember the entire content of the input within this vector.

Once we have encoded the entire source input, we can then use this encoded vector to predict the first token of the output. This is generally done by defining the first hidden vector for the output  $\mathbf{h}_{y,0}$  to be equal to the final vector of the input  $\mathbf{h}_{x,|\mathbf{x}|}$ , then multiplying it with another weight vector used for prediction to calculate a score  $\mathbf{g}$  for each token in the output vocabulary:

$$\mathbf{g}_1 = W_{\text{pred}}\mathbf{h}_{y,0} + \mathbf{b}_{\text{pred}}. \quad (7)$$

We then predict the actual probability of the first token in the output statement, for example “return”, by using the *softmax* function, which exponentiates all of the scores in the output vocabulary and then normalizes these scores so that they add to one:

$$P(y_1 = \text{“return”}) = \frac{\exp(g_{\text{return}})}{\sum_{\tilde{g}} \exp(\tilde{g})}. \quad (8)$$

We then calculate a new hidden vector given this input:

$$\mathbf{h}_{y,1} = \text{encode}(y_1 = \text{“return”}, \mathbf{h}_{y,0}). \quad (9)$$

We continue this process recursively until we output a special “end of hunk” symbol “</s>”.

**Why neural MT models?:** As mentioned briefly in the intro, neural MT models are well-suited to the task of automatic patch generation for a number of reasons. First, they are an end-to-end probabilistic model that can be trained from parallel datasets of pre- and post-correction code without extra human intervention, making them easy to apply to new datasets or software projects. Second, they are powerful models that can learn correspondences on a variety of levels; from simple phenomena such as direct token-by-token matches, to soft paraphrases [63], to weak correspondences between keywords and large documents

2. This represents a simple recurrent neural network, but in our actual model we use a more sophisticated version of encoding function called “long short-term memory” (LSTM), which performs better on long sequences [62].

for information retrieval [64]. Finally, they have demonstrated success in a number of code related tasks as iterated at the beginning of this section, which indicates that they should be useful as part of bug fixing algorithm as well.

**Attention:** In addition, we use a neural MT model with this basic architecture, with the addition of a feature called *attention*, which, put simply, allows the model to “focus” on particular tokens in the input  $x$  when generating the output  $y$  [61], [65]. Mathematically, this corresponds to calculating an “attention vector”  $a_j$ , given the input hidden vectors  $h_x$  and the current output hidden vector  $h_{y,j}$ . This vector consists of values between zero and one, one value for each word in the input, with values closer to one indicating that the model is choosing to focus more on that particular word. Finally, these values are used to calculate a “context vector”

$$c_j = \sum_{i=1}^{|\mathbf{x}|} \alpha_{j,i} h_{x,i}, \quad (10)$$

which is used as additional information when calculating score  $g_j$ . Attention is particularly useful when there are many token-to-token correspondences between the input and output, which we expect to be the case for our patch generation task, where the input and output code are likely to be very similar. This attention model can be further augmented to allow for exact copies of tokens [66], or be used to incorporate a dictionary of common token-to-token correspondences (copies or replacements) [67]. In our model, we use the latter, which allows us to both capture the fact that tokens are frequently copied between pre- and post-correction code, and also the fact that some replacements will be particularly common (e.g. `loadBalancerType` to `setLoadBalancerType`).

**Implementation Details:** As a specific implementation of the neural MT techniques listed above, we use the `lamtram` toolkit [68]. For reproducibility, we briefly list the parameters below, and interested readers can refer to the references for detail. As our model we use an encoder-decoder model with multi-layer perceptron attention [61] and input feeding [65], with encoders and decoders using a single layer of 512 LSTM cells [62]. We use the Adam optimizer [69] with a learning rate of 0.001 and minibatch size of 2048 words, and decay the learning rate every time the development loss increases. To prevent overfitting, we use a dropout rate of 0.5 [70]. To generate our outputs, we perform beam search with a beam size of 10.

## 4 APPROACH

The idea of corrective patch generation using NMT considers code changes as translation from pre-correction code to post-correction code. Figure 2 provides an overview of our system, `Ratchet`, which consists of two main parts: creating the training corpora, and generating patches using the trained model. In this paper, we target Java source code and focus on changes within Java methods. Particularly, the granularity of code we target is a statement similar to the previous study [51].

### 4.1 Extracting Change Hunks from Code Repositories

In order to create our training corpora, we start by extracting pre- and post-correction statements using a sequence of steps. We detail each of these steps in the following text:

**Preparing Histrorage for method-level histories.** Since the software repositories store the code modifications at the commit level, our first step is to transform these commits into method-level modifications. To do so, we convert the existing code repositories to `histrorage` repositories [71]. `Histrorage` creates a new repository that stores all methods in the logs of the original repository as individual Git objects. In essence, `histrorage` is a Git repository that allows us to operate any Git commands as usual<sup>3</sup>.

**Collecting the modified methods.** We use the command `git log --diff-filter=M` on the `histrorage` repositories to collect all modified methods in the entire history. The option `--diff-filter=M` will provide only modified (M) files, which are methods in `histrorage` repositories. Since we are interested in training our model on pre- and post-correction statements, we only consider methods that modify code, i.e., not methods that are newly created or completely deleted.

**Identifying change hunks.** As stated in Section 2, a change hunk is a pair of pre-correction and post-correction statements. We identify these change hunks from the outputs of the `git diff`. Since we assume pre-correction statements have been corrected to post-correction statements, we need to identify the corresponding line pairs appropriately<sup>4</sup>.

### 4.2 Preprocessing the Statement Corpora

Before storing the statement pairs as pre-correction and post-correction statement corpora, we perform the following preprocessing steps. As seen in Figure 2, the same processes will be applied to query statements except for the step (6) and (7), which are needed only for creating the corpora.

**(1) Limit to single-statement changes and single-statement queries.** In this study, we only consider single-statement (one-line) changes. We do so for the following three reasons. First, previous studies showed that most reusable code is found at the single-statement level [51], [74]. Second, it is difficult to treat multiple statement changes (one-to-many, many-to-one, and many-to-many statement changes) for identifying pairs. Those multiple statement changes can have inappropriate corresponding statements. For example, if there exists one pre-correction statement and two post-correction statements in one change hunk, this change can be a single-statement change and one independent statement insertion. If we consider these statements one pair, the independently inserted statement can be noise in the training data. Third, it is difficult to manage past histories associated with multiple statements. Using the command `git blame` on `histrorage`, we identify commits on

3. We used a tool, called `kenja` [72] (<https://github.com/niyaton/kenja>) to prepare the `histrorage` repositories. Converted `histrorage` repositories are now hosted in `Codosseum` Web service: <http://codosseum.naist.jp/>, which is previously presented as `Kataribe` [72], [73].

4. The options `--histogram`, `--unified=0`, `--ignore-space-change`, `--ignore-all-space`, and `--ignore-blank-lines` are used to apply an advanced diff algorithm, ignore unchanged statements, and ignore trivial changes.

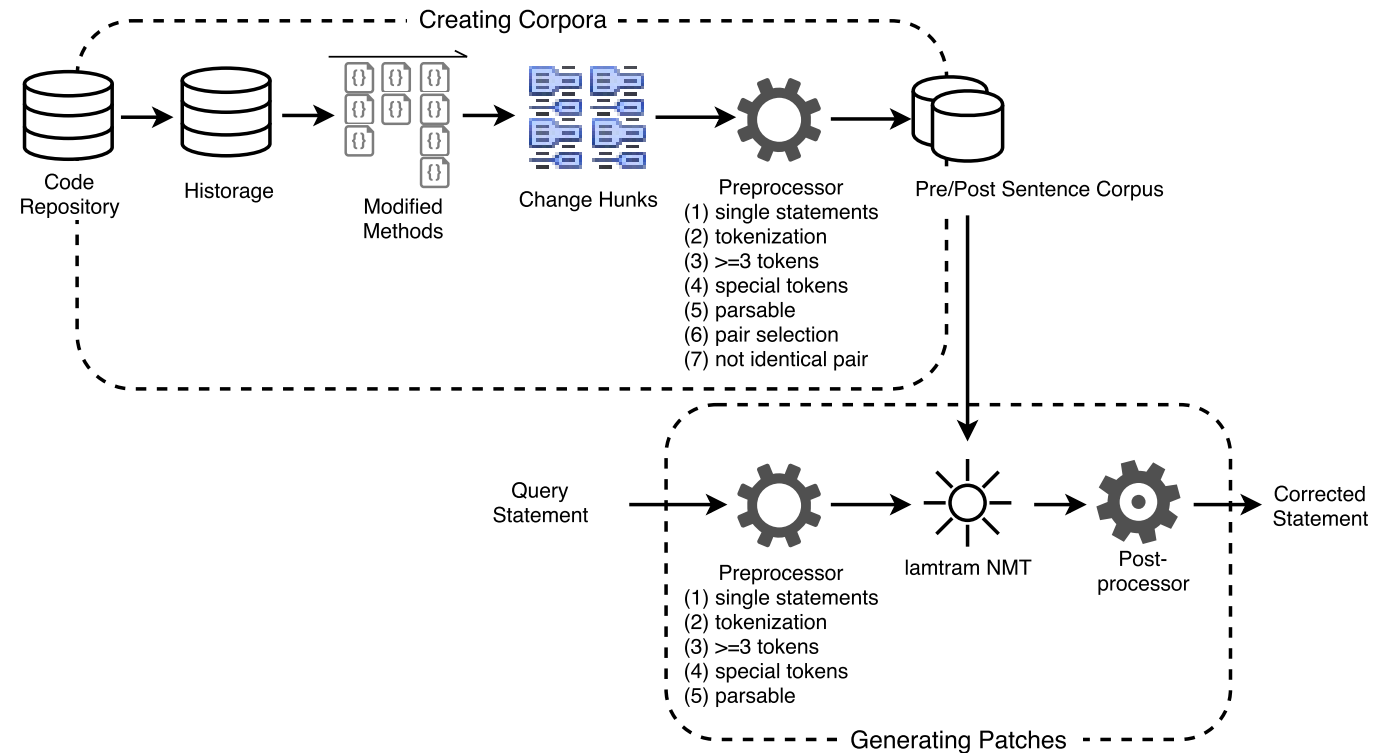


Fig. 2. Overview of Ratchet, an NMT-based corrective patch generation system.

which deleted lines initially appeared. In general, multiple statements can have different past histories, which makes it difficult to treat those multiple statements as one unit. For all statement pairs, we collect past history information including the original commit, changed year and deleted year, to be used for our experiments. Although we apply this filtering, we found that single-statement changes are the majority in our change hunks (as we show later in Figure 3 and Table 2).

(2) **Tokenize statements.** Since the NMT model requires separate tokens as input, we use the `StreamTokenizer` to tokenize the Java statements.

(3) **Remove statement pairs or statement queries with less than three tokens.** We remove statements that have very few tokens (i.e., less than 3) since they are less meaningful. Our observations indicate that most such lines only contain opening or closing parenthesis.

(4) **Replace the contents of method arguments with a special token.** From our many trials, we realized that a wide variety of the contents of method arguments make it difficult to generate corresponding contents. This is because sometimes method argument contents include tokens that rarely appear. We replace method and array arguments with a special token, `arg` and `val`, respectively.

(5) **Filter unparseable statement pairs and queries.** There exist incomplete statements in our collected statements, e.g., when there is a long statement that is written across two lines, and only one line is changed. To remove these incomplete Java statements, we put each statement in a dummy method of a dummy class, and try parsing the class to get an AST using `JavaParser`<sup>5</sup>. If we fail to parse

classes with either pre- or post-correction statements, we filter out the failed statement pairs.

(6) **Select post-correction statements from multiple candidates.** This step is performed to address *the nature of sequential order* in documents. After collecting all pre- and post-correction statements from the entire history of a code repository, we can have statement pairs that have the same pre-correction statements but different post-correction statements. In order to allow the NMT models to effectively extract relationships or patterns, we chose only one post-correction statement for one pre-correction statement, and remove all other post-correction statements. The idea behind this selection is that it is better to learn from recently and frequently appearing statements. Given a pre-correction statement, we obtain post-correction statements that appeared in the most recent year. Then, from those newer statements, we select statements that most frequently appeared in the entire history. If we cannot break ties, we select the first statement in alphabetical order to make the process deterministic.

(7) **Remove identical pre- and post-correction statements.** After the above processes, there exist pairs of identical pre- and post-correction statements. For example, statement pairs from changes only within method arguments, and white space changes. We remove those statement pairs.

### 4.3 Post-Processing

Since we replace the contents of method arguments and replace it with a special token, the NMT model does not generate method arguments. However we expect that the method arguments of a query statement can be reused in the generated statement. Therefore we prepare the following heuristics for new method arguments.

5. `JavaParser`: <http://javaparser.org/>

TABLE 1

Descriptive statistics of the studied systems. The number of Java files and methods are from the latest snapshots.

Project	Period	# of Commits	# of Files	# of Methods
ambari	Aug-11 to Apr-17	14,042	2,719	29,212
camel	Mar-07 to Jun-17	28,668	16,889	92,839
hadoop	May-09 to Oct-14	8,323	5,696	21,292
jetty	Mar-09 to Apr-16	14,167	2,668	21,172
wicket	Sep-04 to Jun-17	19,960	5,039	16,049

TABLE 2

Statistics of change hunks in the entire period.

Project	# of		#, (%) of Hunks with single-statement pairs
	All hunks		
ambari	13,701	8,565	(62.5%)
camel	43,237	28,672	(66.3%)
hadoop	30,806	21,049	(68.3%)
jetty	38,443	25,517	(66.4%)
wicket	32,132	21,926	(68.2%)

- Methods that have the same name will have the same method arguments.
- For chained method calls, arguments are assigned in the same order.
- If no method argument content is left in a query statement, leave the remaining method call arguments empty.

The `lamtram` toolkit provides scores associated with generated statements with the logarithm of a posteriori probability of output E given input F as  $\log P(E|F)$ . Those scores can be considered as confidences of the results. We empirically determine thresholds and ignore the generated statements with low scores. In addition, we can also ignore invalid generated statements that cannot be parsed.

## 5 EXPERIMENTAL SETUP

In this section, we discuss our dataset and the design of our experiment. Particularly, we are interested in examining the viability of our approach in generating bug-fixing statements. To do so, we need to identify bug-fixing statement pairs. We discuss the tool used to identify the bug-inducing and bug-fixing commits that are used to determine our bug-fix statement pairs. Then, we provide descriptive statistics about the studied datasets.

### 5.1 Subject Projects

To perform our case study, we study five projects, namely Apache Ambari, Apache Camel, Apache Hadoop, Eclipse Jetty and Apache Wicket. We chose to study these five projects since they have a long development history and are large projects that contain many commits. Table 1 shows the period considered, the number of commits, files and methods in our dataset.

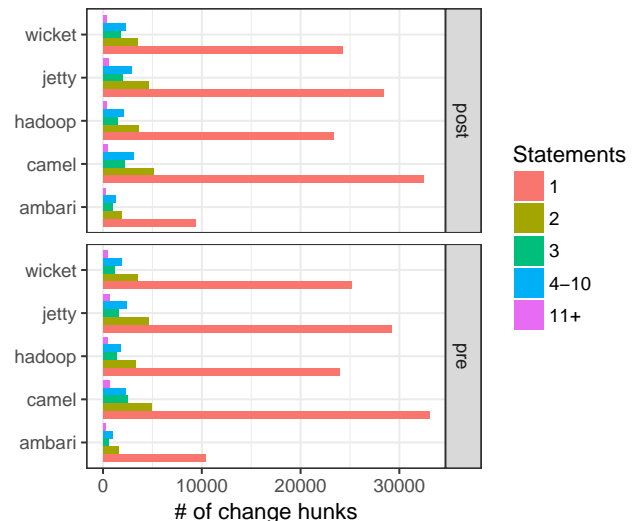


Fig. 3. The number of change hunks with different numbers of pre- and post-correction statements in the entire periods.

Figure 3 shows the distribution of the number of pre- and post-correction statements in all change hunks. We find that most of changes are single statements in either insertion, deletion, or modification. Multi-statement changes are not frequent. Table 2 shows the number of all change hunks and the number of change hunks that are derived from single-statement changes. We see from the table that approximately 62 – 68% of the changes are single-statement changes. This ratio of single-statement changes shows that although our NMT-based technique may not be applied to all changes, it is applicable to the majority of the changes.

### 5.2 Experimental Design

From the collected pre- and post-correction statements, we prepare the training data (Table 3) and testing data (Table 4). Considering the number of statements, we set the testing year for each project as shown in Table 4. All statement pairs in each testing year are used as testing data, which means we chose statement pairs whose pre-correction statements are created in the testing year and changed to the corresponding post-correction statements in the same testing year. All years before the testing year are considered as training periods. In each training period, the numbers of statement pairs, whose pre-correction statements are changed to post-correction statements in the training period, are shown in Table 3.

This experimental design can be regarded as a simulation of generating corrected statements only by learning past histories when new statements are created and they will be modified soon (in the same year). If this works, we can prevent recurring or similar issues before being inserted into the code, or even when the code is being edited.

### 5.3 Data Preparation

Table 3 details the impact of the various preprocessing steps on our approach. The before filtering row shows the number of all single-statement change pairs. The  $< 3$  tokens row shows the effect of removing statements that have less

TABLE 3  
Filtering results for training data.

	ambari		camel		hadoop		jetty		wicket	
train period	2011-2013		2007-2013		2009-2012		2009-2013		2004-2014	
#, (%) of statement pairs										
before filtering	4,253	(100%)	25,562	(100%)	11,952	(100%)	21,278	(100%)	21,268	(100%)
(3) <3 tokens	70	(1.7%)	285	(1.1%)	69	(0.6%)	281	(1.3%)	127	(0.6%)
(5) not parsable	261	(6.2%)	2,924	(11.4%)	1,239	(10.4%)	2,023	(9.5%)	3,092	(14.5%)
(6) lost candidates	88	(2.1%)	1,489	(5.8%)	384	(3.2%)	1,186	(5.6%)	1,324	(6.2%)
(7) identical	2,353	(55.3%)	11,346	(44.4%)	5,812	(48.6%)	7,755	(36.4%)	7,068	(33.2%)
final statement pairs	1,481	(34.8%)	9,518	(37.2%)	4,448	(37.2%)	10,033	(47.2%)	9,657	(45.4%)

TABLE 4  
Summary of testing data.

	ambari	camel	hadoop	jetty	wicket
test year	2014	2014	2013	2014	2015
NU	6	42	29	149	7
UQ	30	54	167	31	16
UR	0	8	15	13	1

than 3 tokens. Then we remove the unparseable statements in both, pre-correction and post-correction statements. The final step removes identical statement pairs in the pre- and post-correction statements. The last row shows the final number of statements used in our study.

In addition, we perform specific processing for the training and testing data, which we detail below:

**Replacing rare tokens in the training data.** From the processed statement pairs, we prepare pre-correction statement corpus and post-correction statement corpus. For each corpus, tokens that appear only once are replaced with `<unk>`, which is a common way to handle unknown tokens [55]. This script is available in the lamtram toolkit<sup>6</sup>.

**Categorization of testing data.** When testing our approach, we call the pre-correction statements in the testing data as *queries*. On the other hand, we call the post-correction statements as *references*.

When we evaluate our approach, we separate the testing data with their characteristics. First, all statement pairs in the testing data are divided into bug-fix statement pairs and non-bug-fix statement pairs. This classification procedure is presented in Section 5.4. Then both classes of statement pairs are categorized into three:

NU: **No unknown.** There are no unknown tokens in a statement pair. All tokens in a query statement appear in the pre-correction statement from the training data corpus, and all tokens in a reference statement appear in the post-correction statement of the training data corpus.

UQ: **Unknown in query.** One or more token(s) in the query statement do not appear in the pre-

correction statement corpus. In other words, there are unknown tokens in the query.

UR: **Unknown in reference.** Although there is no unknown token in the query statement, there are one or more unknown token(s) in the reference, i.e., in the corresponding post-correction statement.

We categorize the statements as shown above to know which data can be used in our experiments. This is particularly important since the trained NMT models have not seen *unknown* tokens during training, addressing queries in UQ or UR is very difficult. In fact, it is impossible for the NMT models to generate statements that are the exact same as the references for the UR category.

Table 4 shows the number of statement pairs for these categories of bug-fixing and non-bug fixing classes. As can be seen from the Table 4, the majority of the training data’s statements fall in the UQ category (except for the Jetty project). On the other hand, the good news is that statements in the UR category are the least. We evaluate our approach using statements in the NU category.

The dataset is available online<sup>7</sup>.

## 5.4 Identifying Bug-Fixing statements

We collect bug-fixing statement pairs by identifying the pairs of bug-inducing and bug-fixing commits. To obtain these commits, we use `Commit.guru` [75]<sup>8</sup>, a tool that analyzes and provides change level analytics. For full details about `commit.guru`, we point the reader to the paper by Rosen *et al.* [75], however, here we describe the relevant details for our paper. `Commit.guru` takes as input a Git repository address, an original code repository in this study, and provides data for all commits of the project. It applies the SZZ algorithm [76] to identify bug-inducing commits and their associated bug-fixing commits. In addition, `Commit.guru` provides a number of change level metrics related to the size of the change, the history of the files changed, the diffusion of the change and the experience of the developers making the modification.

As mentioned earlier in step (1) of preprocessing (Section 4.1), we have meta information of statements including

<sup>7</sup>. Train and test dataset for this study: <https://github.com/hideakihata/NMTbasedCorrectivePatchGenerationDataset>

<sup>8</sup>. Commit Guru: <http://commit.guru>

<sup>6</sup>. lamtram: <https://github.com/neubig/lamtram>

TABLE 5  
Amount of the generated valid statements.

ambari	camel	hadoop	jetty	wicket
6/6	42/42	28/29	147/149	7/7
(100%)	(100%)	(97%)	(99%)	(100%)

the original commits of post-correction statements and the original commits of pre-correction statements. We consider a pair of statements bug fixing if and only if a pre-correction statement is created in a bug-inducing commit and an post-correction statement is created in the associated bug-fixing commit<sup>9</sup>. The other statement pairs are treated as non-bug-fix statements. We do not distinguish the types of the training data, that is, bug-fix or non-bug-fix. This is because we prefer to increase the training data available to the model and make the model learn from all varieties of changes.

## 6 EVALUATION

We evaluate the performance of Ratchet with respect to two aspects: accuracy and usefulness of generated statements. In all of the results presented in this section, the NMT models are trained and tested with data from the same project (i.e., within-project evaluation).

### Can the models generate valid statements?

Table 5 shows the number (and percentage) of generated valid statements. We do not use thresholds here, that is, all generated statements including low scores are considered. As we see from the table, in most cases the models generated valid and complete Java statements. These high accuracy results are especially interesting since we did not explicitly teach the models the Java language specification. Simply, the models were able to achieve this high level of performance by themselves, using approx. 1,500 to 10,000 statement pairs.

In most cases of the five projects nearly 100% of the generated statements are valid Java statements. In total the models generated 230 valid statements for 233 queries (98.7%).

### How accurate are the generated statements?

In this section we evaluate the accuracy in a strict manner, that is, only generated statements that are **identical to references** are considered as correct. Our results are based on the NU (no unknown) category of statements, since as mentioned earlier, other categories are difficult (impossible for UR) to generate accurate statements that are identical to the reference statements.

Before analyzing accuracy, we categorize outputs as the following three types:

- **Correct:** a generated statement is identical to the reference.

<sup>9</sup> Commit IDs in a historage and the corresponding commit IDs in the original Git repository are different because the contents are different. But we can trace the corresponding original commit IDs from historage since they are written in `git notes` of historage.

TABLE 6  
Fix generation and Plastic Surgery for *buggy* queries. Contents of method arguments are ignored. Threshold is -0.7. Bold indicates win in comparison.

		Ratchet			Plastic Surgery		
amb.	correct	2	■ (33%)		2	■ (33%)	
	incor.	0	(0%)		0	(0%)	
Pr, Re, F		1.00	0.33	0.50	1.00	0.33	0.50
cam.	correct	28	■ (67%)		3	■ (7%)	
	incor.	2	■ (5%)		1	■ (2%)	
Pr, Re, F		<b>0.93</b>	<b>0.67</b>	<b>0.78</b>	0.75	0.07	0.13
had.	correct	10	■ (34%)		10	■ (34%)	
	incor.	10	■ (34%)		10	■ (34%)	
Pr, Re, F		0.50	0.34	0.41	0.50	0.34	0.41
jet.	correct	112	■ (75%)		112	■ (75%)	
	incor.	9	■ (6%)		11	■ (7%)	
Pr, Re, F		<b>0.93</b>	0.75	<b>0.83</b>	0.91	0.75	0.82
wic.	correct	5	■ (71%)		5	■ (71%)	
	incor.	0	(0%)		0	(0%)	
Pr, Re, F		1.00	0.71	0.83	1.00	0.71	0.83

- **Incorrect:** a generated statement is not identical to the reference.
- **NA:** a generated statement is invalid or identical to the query, or its score is lower than a threshold.

To measure the accuracy of generated results, we compute precision, recall, and  $F_1$ , which are defined as:  $precision = \frac{\#correct}{\#provided}$ ,  $recall = \frac{\%correct}{\#queries}$ , and  $F_1 = \frac{2 \times precision \times recall}{precision + recall}$ , where  $\#provided$  is the sum of  $\#correct$  and  $\#incorrect$ . Higher precision indicates that the provided results are correct. Higher recall means that the results contain less NA but many correct. Providing a small number of results with high confidence can improve precision but lower recall. Since there is a tradeoff between precision and recall,  $F_1$ , the harmonic mean of precision and recall, is also presented.

We compare the accuracy of our NMT models with the previous state-of-the-art. Particularly, we compare to the Plastic Surgery approach [51], i.e., patch recommendation with line-granular snippets that already exist in the training data. To do so, we examine whether a query statement exists in the pre-correction statement training data corpus, and if it does, we check whether the corresponding post-correction statement also exists (in the training data). If this happens, then we consider the statement to be covered by the Plastic Surgery approach. If there is no identical pre-correction statement, we mark the result as NA.

When evaluating Ratchet and as stated in Section 4.3, we use a threshold to ignore results with low confidence. Figure 4 illustrates the transitions of  $F_1$  values with different thresholds (from -1.2 to -0.1). The solid lines are  $F_1$  values of Ratchet and the dotted lines are  $F_1$  values of the Plastic Surgery approach, which do not change with thresholds. We find that  $F_1$  values slightly change when we vary the



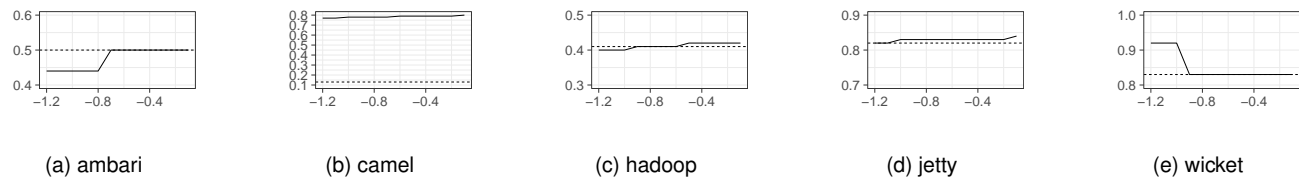


Fig. 4.  $F_1$  values with thresholds (-1.2 to -0.1). The solid lines are  $F_1$  values of Ratchet and the dotted lines are  $F_1$  values of the Plastic Surgery approach.

thresholds. Lowering thresholds improves recall, however, it impacts the precision in the opposite direction. On the other hand, raising the threshold improves precision but makes recall worse<sup>10</sup>. Based on our analysis of the threshold, we empirically set the threshold as 0.7 for the analyses that follow.

Since Ratchet does not generate the contents of method arguments, we first evaluate the accuracy by ignoring those contents. To be fair, we also apply the same condition when evaluating the Plastic Surgery approach. Table 6 shows the results of our approach and compares it with the results with Plastic Surgery. We observe that the Plastic Surgery hypothesis holds in many cases, that is, changes (corrections) contain snippets that already exist in code repositories at the time of the changes, and these snippets can be efficiently found and exploited [51].

That said, Table 6 shows that Ratchet improves the results in two projects and does not change in three projects. We observe that in camel, the results are greatly improved: 28 correct statements are generated compared with three patterns matching using the Plastic Surgery approach. Our results show that the NMT models work, as well as Plastic Surgery, if there are easily exploited statement-level patterns (i.e., reusable snippets), and works better than Plastic Surgery if there exist only finer-grained exploited patterns (i.e., fine-grained fixing patterns), which Plastic Surgery cannot use.

Table 7 presents examples of generated fixes that cannot be fixed by Plastic Surgery, but have a fix generated with our models. Sometimes the model learns the incrementation of value (query 1). Generics-related fixes are typical examples of successful generation with the NMT models (query 2 and 3). Sometimes it is preferred to remove `this` (query 4) if it makes the style consistent with the styling used in the specific project. In fact, our models learned to remove the keyword ‘this’ because similar patterns were prevalent in the project’s history.

NMT-based patch generation works better than Plastic Surgery, achieving  $F_1$  values between 0.41 to 0.83 for buggy queries. In total 157 correctly generated statements without method arguments, the contents of method arguments for 141 statements (89.8%) are correctly provided by reusing the contents of method arguments in queries.

10. The data of wicket is an exception, in which we can find a correct result without increasing incorrect statements when lowering the threshold.

### Can the generated statements help in correction?

During the previous evaluation of accuracy, we considered the generated statements to be correct only if they are *identical to the reference statements*, otherwise they are considered to be incorrect or NA. To investigate whether the generated statements are useful, even if they are not identical to actual future corrections, we also perform a human evaluation with such (non-identical) corrections.

We show survey participants the following three code snippets for one fix: i) an original problematic code snippet (before correction), ii) the actually fixed code snippet (after correction), and iii) a code snippet that is proposed as a fix by our NMT models. All code snippets contain one type of buggy or fixed statements with the surrounding statements<sup>11</sup>.

From the five projects, we collect ten corrections including five correctly and five incorrectly generated statements in the NU (no unknown) category, which are evaluated in Table 6 and Table 9. In addition, we collect five fixes that belong to the UQ (unknown in query) or the UR (unknown in reference) categories, which are known to be difficult for NMT models to generate. For simplicity, we call the above three groups *correct fixes*, *incorrect fixes*, and *challenging fixes* respectively.

For each correction we prepare the following four statements, and ask the participants to evaluate using a five-level Likert scale scores from 1 (strongly disagree) to 5 (strongly agree) whether: (a) *The proposed fix helps you to understand the required change*, (b) *The proposed fix can be a reference if you were to create your own fix*, (c) *The proposed fix is harmful or confusing*, and (d) *The proposed fix does not make sense and I will just ignore it*. We asked not only positive impressions but also negative impressions in order to assess the usefulness and potential risks of incorrect generation. The survey material is available online<sup>12</sup>.

We recruited participants in Canada, US, and Japan, and 20 people participated in the survey including five undergraduate, 14 graduate students, and one professor. As Siegmund *et al.* reported that self estimation seems to be a reliable way to measure programming experience [77], we asked the participants to estimate their experience in both, overall and Java programming experience. The participants can select any of 5 choices, varying between 1 (very inexperienced) to 5 (very experienced). Those who score 4 or 5 in both self estimation are considered to be *high-experienced*

11. One case has two buggy or fixed statements that are similar to each other, and others only have one statement of buggy or fixed statement.

12. Survey material for human evaluation: <https://tinyurl.com/RachetSurvey>

TABLE 7  
Examples of generated statements that cannot be fixed by the Plastic Surgery approach.

Query statement	Generated statement
1. <code>commands [ 10 ] = this . passwordFile . toString ( ) ;</code>	<code>commands [ 11 ] = this . passwordFile . toString ( ) ;</code>
2. <code>List body = assertInstanceOf ( arg† ) ;</code>	<code>List &lt;? &gt; body = assertInstanceOf ( arg† ) ;</code>
3. <code>Set &lt; String &gt; knownRoles = new HashSet ( ) ;</code>	<code>Set &lt; String &gt; knownRoles = new HashSet &lt;&gt; ( ) ;</code>
4. <code>return this . height ;</code>	<code>return height ;</code>

arg†: `List . class , result . getExchanges ( ) . get ( 0 ) . getIn ( ) . getBody ( )`

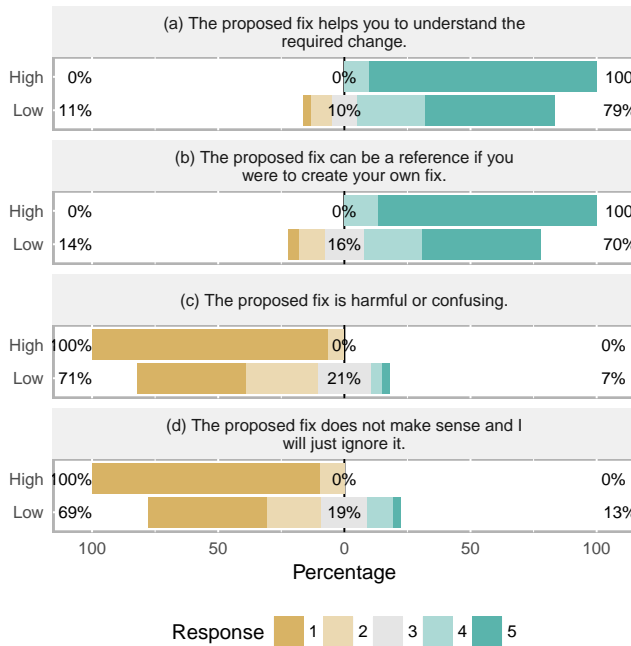


Fig. 5. Survey results of five *correct* fixes. Responses are Likert scale from 1 (strongly disagree) to 5 (strongly agree).

and others are considered to have *low*-experience. Five in six high experienced participants have more than five years of development experience, and the other have three-to-five years of experience. In 14 low-experience participants, the experience periods vary from less than one year, one-to-three years, three-to-five years, and more than five years.

Figure 5 shows the result of the *correct* fix group. The results shown in the figure show that the generated statements are useful. All high-experience and most of the low-experience participants agreed (scores 4 or 5 for questions (a) and (b)) that the correct fix statements helped them and that the statements and did not have negative effects (i.e., most scores are 1 or 2 for questions (c) and (d)).

Figure 6 shows the results of the *incorrect* fix group, which includes statements with incorrect method calls and/or incorrect generic types, for example. We assumed that these fixes are harmful or confusing because they tend to be partially the same as the references, but are slightly different from the actual fixes. However, as evidenced by the results shown in Figure 6, the majority of highly and low experienced participants agree to that such imperfect statements may still be helpful (i.e., by providing positive answers to statement (a) and (b)). Although the highly

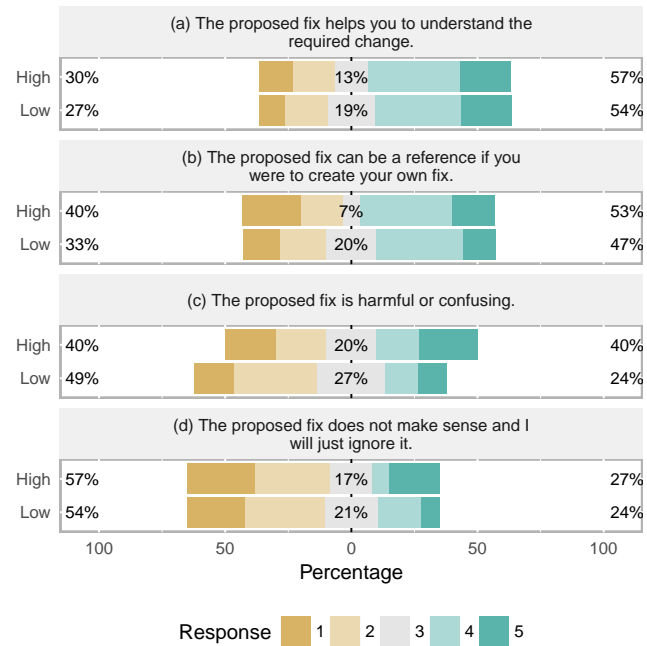


Fig. 6. Survey result of five *incorrect* fixes with six high and 14 low experienced participants.

experienced participants tend to consider such imperfect statements harmful or confusing (highly experienced agreed 40% and low experienced agreed 24%), both high and low experienced participants did not consider the proposed fix did not make sense.

The following are some comments we received: “A *potentially better fix than original*,” “I prefer having a ‘this’ but this is personal preference,” “The word ‘info’ seems more clear than ‘trace.’ Good change,” and “Changed to a *wrong direction*.” One participant pointed out that the proposed fixes seem to provide several pieces of information, for example, the location of fix, the need of initialization of methods, and types for generics. S/he claimed that this information is useful if s/he knows the context of the code, even if an error exists. We find that even for the same fixes, some participants perceived them differently, from which we can infer that sometimes better fixes depend on preferences and/or the context.

Figure 7 shows the result of the *challenging* fix group. The fixes belonging to this group are difficult to generate because of unknown terms, which means that the queries and correct answers are mostly unseen by the models. Therefore we considered that those fixes did not make sense

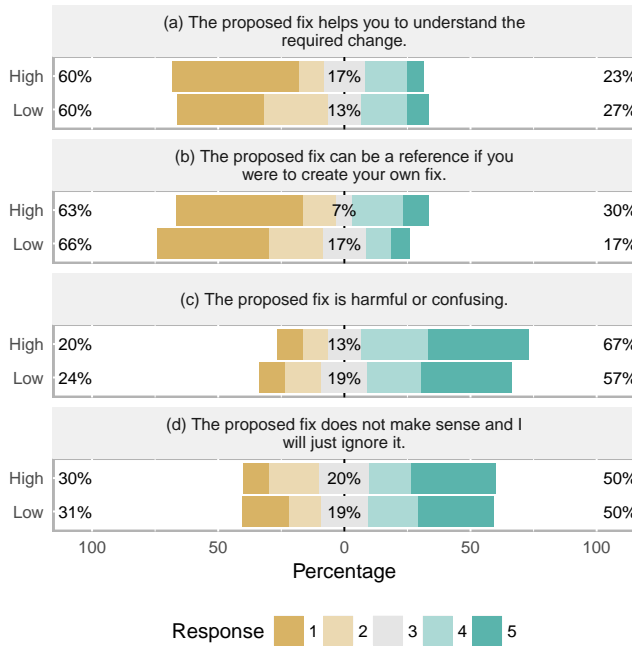


Fig. 7. Survey result of five *challenging fixes* with six high and 14 low experienced participants.

and did not provide any useful information. One case is changing `BigInteger` to `toHexString`, which even fails the compilation check. A participant left a comment “*I think it would produce more confusion than help.*” As seen from the figure, the majority of both, highly and low experienced participants have negative impressions with regards to such statements. However, some still have positive opinions even for such failure cases. Another case is given a query of `FSDataOutputStream fos = null ;` generating `HdfsDataOutputStream copyError = null ;` while the correct answer is `HdfsDataOutputStream fos = null ;`. This happens because the term ‘`fos`’ does not appear in the target (i.e., post-correction statement) corpus. In the training corpora, there is no statement co-occurring `FSDataOutputStream` with `fos` or `null`. The model learned the replacement of `FSDataOutputStream` and `HdfsDataOutputStream` from the different context of statements. For this case, the participants evaluated more positively than negatively, although there were some comments which stated that the generated statements can be confusing. In sum, we find that even for the challenging fixes, they might be useful.

Even if generated fixes are not identical to actual fixes, they can be helpful because they can suggest the locations of required changes and possible replacements/insertions/deletions. Sometimes better fixes depend on personal preferences or the styles of projects. Although NMT models can learn fine-grained patterns of changes, the lack of information or novel queries are major challenges of fix generation.

TABLE 8  
Summary of testing data from not bug-fixing statements.

	ambari	camel	hadoop	jettty	wicket
test year	2014	2014	2013	2014	2015
NU	64	114	135	151	28
UQ	792	386	1,274	428	99
UR	38	46	113	148	7

TABLE 9  
Fix generation and Plastic Surgery for *non-buggy* queries. Contents of method arguments are ignored. Threshold is -0.7. Bold indicates win in comparison.

		Ratchet			Plastic Surgery		
amb.	correct	13	■ (20%)	11	■ (17%)		
	incor.	10	■ (16%)	17	■ (27%)		
	Pr, Re, F	<b>0.57</b>	<b>0.20</b>	<b>0.30</b>	0.39	0.17	0.24
cam.	correct	36	■ (32%)	34	■ (30%)		
	incor.	31	■ (27%)	25	■ (22%)		
	Pr, Re, F	0.54	<b>0.32</b>	<b>0.40</b>	<b>0.58</b>	0.23	0.39
had.	correct	28	■ (21%)	29	■ (21%)		
	incor.	31	■ (23%)	28	■ (21%)		
	Pr, Re, F	0.47	0.21	0.29	<b>0.51</b>	<b>0.21</b>	<b>0.30</b>
jet.	correct	19	■ (13%)	17	■ (11%)		
	incor.	32	■ (21%)	24	■ (16%)		
	Pr, Re, F	0.37	<b>0.13</b>	<b>0.19</b>	<b>0.41</b>	0.11	0.18
wic.	correct	10	■ (36%)	0	(0%)		
	incor.	3	■ (11%)	3	■ (11%)		
	Pr, Re, F	<b>0.77</b>	<b>0.36</b>	<b>0.49</b>	-	-	-

## 7 DISCUSSION

### 7.1 Generating non-bug-fixing statements

For the accuracy evaluation in Section 6, we only considered bug-fixing statements. Here we investigate the applicability of Ratchet in a more general context, i.e., for non-bug-fixing statements as well. In the same test year, we collected non-bug-fixing statements as shown in Table 8. Again, we use a similar setup as we did for bug-fixing statement evaluations and compare the generated statements with Plastic Surgery outputs.

Table 9 shows the results for non-bug-fixing statements. As we can see from the Table 9, the  $F_1$  values for non-bug-fixing queries ranges between 0.19 - 0.41. These  $F_1$  values are lower than the results obtained for the bug-fixing queries shown in Table 6. That said, we still observe that in all five projects, Ratchet outperforms the Plastic Surgery approach.

One possible explanation for the lower performance is the fact that there are relatively more UQ and UR statement pairs for non-bug-fixing datasets (as seen by comparing Table 4 and Table 8), which indicates the unique nature of non-bug-fix changes.

## 7.2 When/why does NMT fail?

We see that NMT can work better than Plastic Surgery for learning past changes and generating fixes. However, we also find limitations of our approach using NMT for code repository data. We examined some of the cases where our approach failed and discuss the challenges (and possible improvements) from two aspects, modeling and training.

**Modeling:** Although NMT can learn the semantic and structural information by taking global context into consideration [78], some limitations of NMT are known and studied [78], [79].

*Out-of-vocabulary problem* or *UNK problem*. NMT usually uses top-N frequent words in the training data and regards other words as unseen ones, *UNK*. Therefore NMT often makes mistakes in translating low-frequency words [80]. In the context of our fix generation, we find similar issues in low-frequency or novel identifier names, as discussed in the survey result of *challenging fix*. Since those names can be identified from the context, integrating NMT with program analysis could be a promising direction.

*Coverage problem*. NMT lacks a mechanism to guarantee that all words in a source statement are translated, and usually favors short translations. For example, in translation of long method chains with low-frequency tokens, we see insufficient outputs including incomplete statements and disappearing method calls. Moreover, this problem makes it difficult to address larger fix generation for more than one line. As there are several studies trying to address this problem [81], [82], [83], we can consider applying these rapidly developed techniques.

**Training:** In addition to techniques related to NMT, we think there is room for improvement in preparing training data. In this study, we design the experiment as batch learning, that is, whole training data is prepared from the past until the previous year of the test year. However, Barr *et al.* reported that more reusable pieces of code exist in the immediately previous version [51]. Previous studies have tried an online learning setting called training on errors [84], [85]. Applying such online learning could be a promising challenge too.

## 7.3 Threats to Validity

Concerning *external validity*, this study only targets open source projects written in Java. Regarding programming languages, there is a threat of generalization, and it should be interesting to extend this study to other languages.

With respect to *construct validity*, we collect fixes from histories, which can contain mistakes. For example, sometimes fixes can be reverted, but we do not consider such intention. In addition, the SZZ algorithm used for identifying bug-inducing and bug-fixing commits is known to produce errors [86]. Although we do not distinguish buggy and non-buggy changes for training, we classify test data as buggy or non-buggy. This could impact our discussion regarding the type of changes. However, as presented in Section 7.1, Ratchet can work for generation of non-bug-fixing statements as well as bug-fixing statements.

To mitigate threats to *reliability*, we made our dataset and survey material publicly available (see Section 5.3 and Section 6).

## 8 RELATED WORK

Our learning-based patch generation is related to mainly two research areas, namely probabilistic models of source code and change mining, which are for building models by learning and mining data for learning.

### 8.1 Probabilistic Models of Source Code

There are several studies on probabilistic machine learning models of source code for different applications using different techniques. Allamanis *et al.* conducted a large survey on this topic [87]. Table 10 is originally presented in the survey of representative code models [87]. From the original table, non-refereed papers are excluded, some missing papers are added, and the column Data is newly prepared, which summarizes analyzed data in terms of programming languages, data sources, and historical information.

As we see from the table, probabilistic machine learning models have been studied for various applications, such as code completion, code synthesis, coding conventions, and so on. From the point of view of models, newer techniques of neural networks (NN), especially neural sequence-to-sequence models (seq2seq), have not been extensively studied yet. So there are possibilities of extending and improving previous studies applying these models.

From the data column, we see that several programming languages have been studied including Java, C, C#, JavaScript, Python, among others. Although most of studies collected data from code repositories, some used other data sources, for example, programs in TopCorder.com [105], Microsoft Excel help forums [106], Android programming tutorial videos [119], to build probabilistic models of source code. From source code repositories, collecting source code in selected snapshots is a common procedure. However, when considering software evolution, that is, software is updated continuously, learning over long periods is more practical. As discussed in Section 7.2, online machine learning is one of challenges in this scenario. Previous studies demonstrated learning methods in long periods, called training on errors [84], [85]. This can be a good hint for future research on online machine learning of patch generation.

### 8.2 Change Mining

Analyzing and exploiting historical change patterns is another similar topic to this work. Kim *et al.* proposed bug finding techniques based on textual code change histories [120]. From the analysis of open source repositories, they reported that a large amount of bugs appeared repeatedly. From the analysis of graph-based object usage models, Nguyen *et al.* also reported recurring bug-fix patterns and demonstrated fix recommendation based on those patterns [121]. To make use of similar code changes, Meng *et al.* proposes a tool called LASE for creating and applying context-aware edit scripts [122]. LASE analyzes AST-level changes and generates AST node edit operations. From a large-scale study of AST-level code changes in multiple Java projects, Nguyen *et al.* reported that repetitiveness is high for small size changes and similar bug-fix changes repeatedly occurred in cross projects [74]. Barr *et al.* studied the Plastic Surgery hypothesis, that is, same changes already

TABLE 10

Studies on source code generating models. The column *Data* is presented by the authors and other contents were previously presented by Allamanis *et al.* [87]. Only referred papers are presented.

Study	Representation	Model	Application	Data
Allamanis and Sutton [88]	Token	n-gram	—	Snapshot (Java)
Allamanis <i>et al.</i> [89]	Token + Location	n-gram	Coding conventions	Snapshot (Java)
Allamanis and Sutton [90]	Syntax	Grammar (pTSG)	—	Snapshot (Java)
Allamanis <i>et al.</i> [91]	Syntax	Grammar (NN-LBL)	Code search/synthesis	Stack Overflow (C# and NL)
Bielik <i>et al.</i> [92]	Syntax	PCFG + annotations	Code completion	Snapshot (JavaScript)
Campbell <i>et al.</i> [93]	Token	n-gram	Syntax error detection	Selected versions (Java)
Cerulo <i>et al.</i> [94]	Token	Graphical model (HMM)	Information extraction	Snapshot (Java) and NL
Cummins <i>et al.</i> [95]	Character	NN (LSTM)	Benchmark synthesis	Benchmarks (OpenCL)
Gulwani and Marron [96]	Syntax	Phrase model	Text-to-code	Created (DSL and NL)
Gvero and Kuncak [97]	Syntax	PCFG + Search	Code synthesis	Created (Java and NL)
Hata <i>et al.</i> [85]	Token	Orthogonal sparse bigrams	Bug prediction	Long period (Java)
Hata <i>et al.</i> [98]	Token	Vector space model	Bug prediction	Snapshot (Java)
Hellendoorn <i>et al.</i> [99]	Token	n-gram	Code review	Short period (Java)
Hellendoorn and Devanbu [100]	Token	n-gram (cache)	—	Snapshot (Java)
Hindle <i>et al.</i> [101]	Token	n-gram	Code completion	Snapshot (Java and C)
Hsiao <i>et al.</i> [102]	PDG	n-gram	Program analysis	Snapshot (JavaScript)
Ling <i>et al.</i> [43]	Token	RNN + attention	Code synthesis	Snapshot (Java and Python)
Karavivanov <i>et al.</i> [103]	Token	Phrase	Migration	Snapshot (C# and Java)
Kushman and Barzilay [104]	Token	Grammar (CCG)	Code synthesis	Created (Regex and NL)
Maddison and Tarlow [105]	Syntax with scope	NN	—	TopCoder (C#)
Menon <i>et al.</i> [106]	Syntax	PCFG + annotations	Code synthesis	Excel help forums
Mizuno and Kikuno [84]	Token	Orthogonal sparse bigrams	Bug prediction	Long period (Java)
Nguyen <i>et al.</i> [107]	Token + parse info	n-gram	Code completion	Snapshot (Java)
Nguyen <i>et al.</i> [108]	Token + parse info	Phrase SMT	Migration	Snapshot (Java and C#)
Nguyen and Nguyen [109]	Partial PDG	n-gram	Code completion	Snapshot (Java and C#)
Nguyen <i>et al.</i> [110]	Bytecode	Graphical model (HMM)	Code completion	Android
Oda <i>et al.</i> [111]	Syntax + token	Tree-to-string + phrase	Pseudocode generation	Created (Python and NL)
Rabinovich <i>et al.</i> [45]	Syntax	NN (LSTM-based)	Code synthesis	Snapshot (Java and Python)
Ray <i>et al.</i> [112]	Token	n-gram (cache)	Bug detection	Short period (Java)
Raychev <i>et al.</i> [113]	Token + constraints	n-gram / RNN	Code completion	Android
Raychev <i>et al.</i> [114]	Syntax	PCFG + annotations	Code completion	Snapshot (JavaScript)
Sharma <i>et al.</i> [115]	Token	n-gram	Information extraction	Stack Overflow and Twitter
Tu <i>et al.</i> [116]	Token	n-gram (cache)	Code completion	Snapshot (Java and Python)
Vasilescu <i>et al.</i> [117]	Token	Phrase SMT	Deobfuscation	Snapshot (JavaScript)
White <i>et al.</i> [118]	Token	NN (RNN)	—	Snapshot (Java)
Yadid and Yahav [119]	Token	n-gram	Information extraction	Android tutorial videos
Yin and Neubig [44]	Syntax	NN (seq2seq)	Synthesis	Snapshot (Python and DSL)
<b>Ratchet</b>	Syntax	NN (seq2seq)	Patch generation	Long period (Java)

exist in code histories and those changes can be efficiently found and exploited [51]. From line-granular snippet matching analyses, they reported that changes are repetitive and this repetitiveness is usefully exploitable. Yue *et al.* reported, from an empirical study of large-scale bug fixes, that 15-20% of bugs involved repeated fixes [123].

As these studies presented, using change patterns can be promising. However, from the study of the uniqueness of changes, instead of common changes, Ray *et al.* reported that unique changes are more common than non-unique changes [52]. This implies that simply applying past change patterns has limited capabilities in terms of reuse. As our results demonstrated, NMT-based learning approaches have the ability to address this issue by learning bug-fix correspondences on a variety of levels.

## 9 CONCLUSION

In this paper, we introduced **Ratchet**, an NMT-based technique to generate bug fixes from past fixes. Through an empirical validation on five open source projects, we find that **Ratchet** is effective in generating fixes. Moreover, we show that **Ratchet** can even be used to generate statements for non-bug-fixing statements. We compare **Ratchet** to the Plastic Surgery approach and show that **Ratchet** performs at least as well as the Plastic Surgery approach.

We also investigate cases where **Ratchet** fails and find that **Ratchet**, or more generally NMT, suffers from the out-of-vocabulary problem since it depends on the presence of words in the past to train on. Also, NMT cannot guarantee that all words are covered/translated. These aforemen-

tioned issues are areas that we plan to tackle in future work.

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