Compilation Error Repair: For the Student Programs, From the Student Programs

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ABSTRACT

Compile-time errors pose a major learning hurdle for students of introductory programming courses. Compiler error messages, while accurate, are targeted at seasoned programmers, and seem cryptic to beginners. In this work, we address this problem of pedagogically-inspired program repair and report TRACER (Targeted RepAir of Compilation ERrors), a system for performing repairs on compilation errors, aimed at introductory programmers.

TRACER invokes a novel combination of tools from programming language theory and deep learning and offers repairs that not only enable successful compilation, but repairs that are very close to those actually performed by students on similar errors. The ability to offer such targeted corrections, rather than just code that compiles, makes TRACER more relevant in offering real-time feedback to students in lab or tutorial sessions, as compared to existing works that merely offer a certain compilation success rate.

In an evaluation on 4500 erroneous C programs written by students of a freshman year programming course, TRACER recommends a repair exactly matching the one expected by the student for 68% of the cases, and in 79.27% of the cases, produces a compilable repair. On a further set of 6971 programs that require errors to be fixed on multiple lines, TRACER enjoyed a success rate of 44% compared to the 27% success rate offered by the state-of-the-art technique DeepFix.

CCS CONCEPTS

• **Computing methodologies → Machine translation**; *Neural networks*; • **Applied computing → Computer-assisted instruction**; • **Social and professional topics** → *CS1*;

KEYWORDS

Intelligent Tutoring Systems, Compilation Errors, Automatic Repair, Recommendation Systems

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1 INTRODUCTION

The field of automated code repair has traditionally focused on fixing logical errors, upon being given requirement specifications (such as test-suites), while not paying much attention to compilation errors [14]. This was deemed acceptable, given advancements in compiler techniques which made identifying and fixing compile-time errors by experienced developers relatively straight-forward.

However, as noted by Traver [24], compiler error messages are cryptic, and often an impediment to effective programming for an average programmer. Unfortunately, this issue has been largely ignored by compiler designers and better error messages are usually a low priority feature [24]. For those beginning to learn a new language, and hence unfamiliar with programming constructs of that language, compiler errors can be very confusing and time consuming to fix [6]. This is especially true for those who lack prior experience in any form of programming.

Figures 1 and 2 illustrate actual attempts by students in the very first lab session of an introductory course on C programming, as well as the actual fixes proposed by our method TRACER. The captions list the messages returned by the Clang compiler [12], a popular compiler for the C language. It is clear that the compiler error messages in these examples are not very informative for a student who has just been introduced to the concept of formal programming with datatypes and operators.

In the first case, the error message does not provide any valuable feedback to a student unfamiliar with the concept of pass-by-reference vs pass-by-value. It may be frustrating to the student that a format that is valid for printf (%d, followed by variable name) is being flagged as an error for the scanf invocation. In the second case, the compiler error message may actually mislead the student since the error in the program is the trivial omission of an arithmetic operator whereas the compiler is interpreting it as an illegal function invocation, simply because parentheses are involved.

These gaps arise since compilers messages are written for expert programmers and assume that the programmer has a thorough understanding of advanced concepts such as variable addresses,

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```
1 #include<stdio.h>
2 int main(){
3  int a;
4  scanf("%d", a );
5  printf("ans=%d",
6   a+10);
7  return 0;
8 }
```

```
1 #include<stdio.h>
2 int main(){
3  int a;
4  scanf("%d", &a );
5  printf("ans=%d",
6   a+10);
7  return 0;
8 }
```

Figure 1: Left: erroneous program, Right: fix by TRACER. The compiler message read: *Line-4, Column-9: warning: format '%d' expects argument of type 'int *', but argument 2 has type 'int'.*

```
1 #include<stdio.h>
2 int main(){
3     int x,x1,d;
4     // ...
5     d=(x-x1)(x-x1);
6     return d;
7 }
```

```
1 #include<stdio.h>
2 int main(){
3     int x,x1,d;
4     // ...
5     d=(x-x1)*(x-x1);
6     return d;
7 }
```

Figure 2: Left: erroneous program, Right: fix by TRACER. The compiler message read: *Line-5, Column-11: error: called object type 'int' is not a function or function pointer.*

pointers and function invocation. However, these concepts are generally covered much later in a programming course. Thus, a novice programmer is unable to comprehend the error message or the cause of the error. In our dataset, around half of the students made similar errors and although the fix is simple in all these cases, students did require the help of a teaching assistant to understand the error messages and apply the fixes.

Although it is true that the time taken by students to fix common compile-time errors decreases over time as they get more comfortable with grammar of the language and adapt to the compiler messages, in a typical course, it takes a considerable amount of effort and supervision from teaching assistants who not only have to help students correct mistakes, but also help them understand the cause of the error.

With a move towards Massive Open Online Courses (MOOCs) where thousands of students may enroll, it is infeasible to provide human assistance in this manner, even in the initial phase. Moreover, there is evidence [6, 7] that across such programming courses, the errors made by students in the initial phases are quite similar. This points to a lucrative potential for automating this repetitive and monotonous role played by teaching assistants.

The work of Traver [24] attempts to address this problem by offering more informative error messages that would aid programmers in easier diagnoses. There has also been work on designing custom compilers for novice users [23]. These compilers aim for better error recovery and correction than standard compilers, so as to offer better feedback. However, these require a significant amount of effort from compiler designers, and the effort has to be replicated for every compiler being used. Moreover, studies [15] have shown that additional information in the form of enhanced error messages does not seem to be very helpful, especially for novice programmers.

1.1 Our Contributions

We report TRACER (Targeted RepAir of Compilation ERrors), a method for automatically generating template repairs for buggy programs that face compilation errors. This problem has generated significant interest recently. However, the guarantees offered by existing works [2, 7, 19] are rather modest and simply offer compilable code in a large fraction of instances.

The design of TRACER is based on a realization that the goal of program repair in pedagogical settings is not to simply eliminate compilation errors using any means possible (such as deleting the error line altogether), but rather to reveal the underlying errors to the students, so that they may learn how to correct similar errors themselves in the future [25]. In fact, it may be argued that offering the repaired, compilable program to the student directly, which many existing works do [2, 7, 8], defeats the purpose of learning and may even pose challenges in course evaluations.

The techniques adopted by TRACER for program repair are motivated by a common observation [7, 8] that in practice, programmers (especially novice programmers) use a rather small subset of rules and productions of the entire grammar. Thus, it should be possible to repair an erroneous program by mapping it to a similar program (from past code obtained from students themselves) that is known to be compilable, and hence (at least) syntactically correct.

TRACER offers *targeted* corrections that pinpoint the source of the error, as well as recommends the fix actually desired by the student, thereby offering compilable code as a *by-product.* Figures 1 and 2 demonstrate some of the fixes TRACER can successfully apply to actual programs. To this end, TRACER adopts a modular, three-phase methodology for code repair which involves

(1) **Error Localization**: TRACER locates the line(s) where repair must be performed.
(2) **Abstract Code Repair**: TRACER attempts to identify the intent of student and recommends an abstracted form of the repair to the erroneous line(s), based on sequence-to-sequence prediction techniques that use recurrent neural networks.
(3) **Concretization**: TRACER finally converts the abstract repair into actual code that can be compiled.

The above presents a significant departure from existing works [2, 7, 19], which also adopt deep learning techniques such as recurrent neural networks, but in a very *monolithic* manner. It is common in existing works to simply feed the entire erroneous program into a deep network and expect repairs as an output. In contrast, TRACER's modular approach to error repair offers several key advantages over the state-of-the-art.

(1) To the best of our knowledge, TRACER is the first system to be able to successfully reproduce the exact fix expected by the student on an erroneous program, and not merely reduce compilation errors.
(2) Even when comparing compilation rates, TRACER offers success rates that are far superior to the state-of-the-art.
(3) TRACER offers repairs in both abstract and concretized forms. Depending on the learning objectives set by the instructor, either may be offered to students. In particular, the concretized code may be redacted and just the abstract form offered if it is desired that the student identify the form of the

Table 1: Examples of source-target pairs for single-line errors. Each row describes an actual error case found in our data. The first column describes the (erroneous) source line and its abstraction. The second column describes the target line (extracted from repairs attempted by the student) and its abstraction. Finally, the third column describes the abstract and concrete versions of the top-ranked repair suggested by TRACER. TRACER produced compilable code in all these cases. More importantly in most cases, TRACER is able to predict the exact fix expected by the student. TRACER is robust to even inappropriate (albeit compilable) fixes made by students. For instance, in the example in row 3, the target (student) code will compile with warnings but most likely face runtime errors, but TRACER's top suggestion is the most appropriate fix for the corresponding error.

#	Source-line and Source-abstraction	Target-line and Target-abstraction	TRACER's Top Prediction

1	d = (x-x1)(x-x1);
	INT = (INT - INT)(INT - INT);
		d = (x-x1)*(x-x1);
		INT = (INT - INT)*(INT - INT);
			d = (x-x1)*(x-x1);
			INT = (INT - INT)*(INT - INT);

2	p+'a' = p;
	CHAR + 'LITERAL_C' = CHAR;
		p = p+'a';
		CHAR = CHAR + 'LITERAL_C';
			p = p+'a';
			CHAR = CHAR + 'LITERAL_C';

3	printf(,c,);
	printf(,INT,);
		printf(c);
		printf(INT);
			printf("%d",c);
			printf("%d",INT);

4	if(a[i]==a[j] && i!(==)j)
	if(ARRAY[INT] == ARRAY[INT] &&
	INT !(==) INT)
		if(a[i]==a[j] && !(j==i))
		if(ARRAY[INT] == ARRAY[INT] &&
		!(INT == INT))
			if(a[i]==a[j] && i!=(j))
			if(ARRAY[INT] == ARRAY[INT] &&
			INT != (INT))

5	printf("%d", a + b/6));
	printf("%d",INT + INT/LITERAL_I));
		printf("%d", a + (b/6));
		printf("%d",INT + (INT/LITERAL_I));
			printf("%d", a + b/6);
			printf("%d",INT + INT/LITERAL_I);

6	{ while (a > 0) {
	{ while (INT > LITERAL_I) {
		while (a > 0) {
		while (INT > LITERAL_I) {
			{ while (a > 0) {
			{ while (INT > LITERAL_I) {

error from this feedback rather than simply receive corrected code. This is not possible with existing techniques.

(4) Each of the three phases can be improved upon independently, or be replaced with a different technique, to increase the overall accuracy of the system.

The modular structure of TRACER also helps it harness the power of deep learning techniques in a focused manner. In particular, the abstraction phase implicitly performs a *vocabulary compression* step that greatly eases the working of neural networks.

We note that although we present the TRACER system for a C-programming environment, versions of TRACER may be readily developed for other languages as well. As we shall see, the language specific components of the system are minimal, as is the manual effort required to port the system to a new programming language.

1.2 Organization of the Paper

Section 2 describes the processes adopted to prepare data to train the learning algorithms present in TRACER. Section 3 presents details of various modules that constitute TRACER. Section 4 presents a brief overview of the deep learning techniques used by TRACER. Section 5 presents the results of an extensive evaluation of TRACER on programs taken from an actual introductory programming course. Section 6 presents a more detailed literature review. Sections 7 and 8 then, respectively, outline some future directions for this effort and conclude the discussion.

2 DATA PREPARATION

Since TRACER learns to recommend error repairs from student programs themselves, we obtained student submissions in various lab assignments from the 2015-2016 fall semester offering of an Introductory C programming course (CS1) at the Indian Institute of Technology Kanpur (IIT-K). Below we describe the steps taken to create a training subset for TRACER from these submissions.

2.1 Raw Data Collection

Our data was collected using *Prutor* [5], a system that captures intermediate versions of programs in addition to the final submissions. The system is capable of taking snapshots of the student code at every compilation request, as well as at regular intervals by default. Thus, the system gives us a sequence of programs which track the progress of a student while solving a question.

2.2 Source-Target Pair Identification

Given this raw data, we filtered all code to obtain *source-target* program pairs as follows. We identified successive snapshots of the student code (say C_t and C_{t+1}) such that

(1) Compilation of C_t resulted in at least one compilation error
(2) Compilation of C_{t+1} did not produce any compilation errors

C_t is called the *Source Program* and C_{t+1} is called the *Target Program*. These program pairs were further filtered out to those pairs where the programs C_t and C_{t+1} differ at a single line (single-line edits) and those that differed on multiple lines (multi-line edits).

Ostensibly, the former correspond to programs where the error in the program was confined to a single line whereas in the latter, the errors, and hence the student edits, were present on multiple lines. For single-line edit program pairs, the line in C_t that was changed is called the *Source Line* whereas the same line in C_{t+1} is called the *Target Line*.

For example, in Figures 1 (respectively 2), line number 4 (respectively line number 5) in the left and the right hand programs is the source and the target line for that pair of programs. We only used single-line edit program pairs for training TRACER. However, we do report results on multi-line edit program pairs as well (see Section 3.5).

We notice that we train TRACER only on genuine source-target pairs whereas other approaches such as [7] also use program pairs created by artificially introducing errors into a correct program.

Table 2: Our dataset of single-line errors (singleL)

Lab	# Prog	Topic
Lab 1	524	Hello World
Lab 2	1643	Simple Expressions
Lab 3	1015	Simple Expressions, printf, scanf
Lab 4	901	Conditionals
Lab 5	1104	Loops, Nested Loops
Lab 6	1098	Integer Arrays
Lab 7	1232	Character Arrays (Strings) and Functions
Lab 8	1023	Multi-dimensional Arrays (Matrices)
Lab 9	660	Recursion
Lab 10	466	Pointers
Lab 11	453	Algorithms (sorting, permutations, puzzles)
Lab 12	726	Structures (User-Defined data-types)
Exam	3427	Mid-term and End-term programming tests
Practice	9003	Practice problems released regularly

This alternate approach can be tedious in terms of creating and managing errors. Moreover, it is not clear if this helps the system learn how to predict realistic corrections.

2.3 Dataset Statistics

As mentioned earlier, the dataset of programs on which TRACER is trained and evaluated was collected during an introductory programming course at IIT-K This course was credited by 400+ first year undergraduate students. The course had weekly programming assignments (termed *Labs*). These assignments had a specific theme every week, as described in Table 2, so as to test the concepts taught in the class so far. The assignments were attempted under the invigilation of teaching assistants. Students were allowed multiple submission attempts, with only the last submission being graded. We saved the progressive versions of the attempts made by the student towards solving the problem by passing as many pre-defined test-cases as possible.

For each of these labs, we picked a sample of (P_b, P_c) program pairs as our dataset, where P_b is the "buggy" version of a student program which fails to compile, and P_c is a later "corrected" version of the attempt by the same student which compiles successfully. The second column of Table 2 shows the number of programs for each lab we include in our dataset. The difference between P_c and P_b is the set of changes which were performed by the student on P_b, in order to get the program to compile successfully.

From student submissions, we obtained 23,275 and 17,451 source-target program pairs having single-line and multi-line edits respectively, across the entire run of the semester-long course. As mentioned before, we used only single-line edit pairs to train TRACER. These correspond to programs which require edits to a single line in the erroneous program. However, despite being trained on single-line edit pairs, TRACER can seamlessly handle programs requiring repairs on multiple lines as well by simple invoking TRACER repeatedly to fix individual lines, as described in Section 3.5.

We refer the reader to Figure 3 for an overview of our dataset and also an initial look at the performance of TRACER on this dataset. Table 3a lists all types of compilation errors that were present in at least 50 submissions in our dataset. Figure-3b then charts the frequency of occurrence of all these error types in our training and test sets.

Recall that even though we consider only single-line edit source-target pairs for training, our dataset still contains source programs with multiple compilation errors. Also notice that TRACER does well not only on frequent error types such as missing identifiers (E1), but also very rare ones such as invalid digit in constant (E12).

3 TRACER: AN END-TO-END SYSTEM FOR TARGETED REPAIR OF COMPILATION ERRORS

In this section, we describe the technical details of the TRACER system. For most of this discussion, we will focus only on program pairs that have single-line edits. We will pay special attention to multi-line edit programs in Section 3.5. Recall that for single-line edit program pairs, we can identify a source and a target line, the target line being the fix the student applied to rectify the error in the source line.

TRACER treats compilation-error repair as a sequence prediction problem. Given a source line, TRACER interprets it as a sequence of tokens, and attempts to predict a new sequence of tokens, that hopefully correspond to the target source line. The framework of recurrent neural networks is utilized to implement this. However, several augmentations are required for this strategy to succeed.

In particular, given a faulty program, the task of localizing the error is itself a non-trivial task. Indeed, the line numbers present in compiler error messages often themselves do not pinpoint the locations where changes need to be made. Existing works often choose to avoid this issue by, for example, expecting a neural network to jointly perform error localization and error correction [7].

However, our results show that this monolithic approach can overwhelm the underlying neural network architecture. To remedy this, TRACER performs error localization as a separate, modular step. A side advantage of delinking error localization from error correction is that TRACER is able to use different techniques for error localization and error correction which gives it more freedom whereas works such as [7] are constrained to use the same (joint) technique for the two tasks which may perform sub-optimally on one of the tasks, but nevertheless bring down the performance of the entire system.

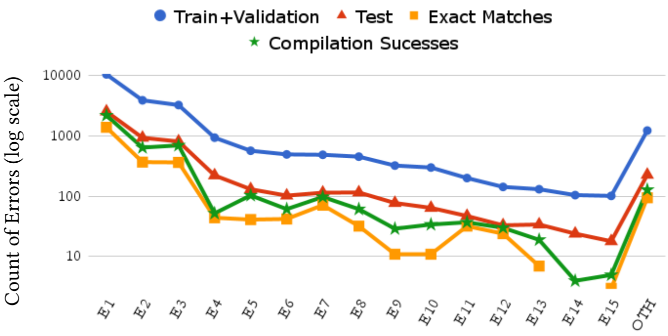
3.1 Error Localization

While the compiler error messages report the exact line of the code which resulted in an error state during compilation, this isn't necessarily the same line where repair needs to be performed. This problem has been addressed by prior work in different ways. [8] targets the exact line number reported by compiler. [20] performs a brute force replacement, starting from the first-statement to the last; relying on their model to regenerate the correct statements, while fixing incorrect ones. [7] trains a deep-network on the entire source-program (encoded with line-numbers) to generate a ranked list of potential lines to focus their repair on.

For error localization, TRACER makes a useful observation: in our dataset of introductory C programs where single-line edits were performed by students, the location of the edits lay very close to the line where the compiler flagged an error. In 87.79% of the cases,

Code	Error Message	Code	Error Message
E1	expected identifier	E9	too few args to func call
E2	undeclared identifier	E10	expected decl or statement
E3	expected expression	E11	called object not a func
E4	extraneous ID	E12	invalid digit in const
E5	incorrect assignment	E13	too many args to func call
E6	re-definition of ID	E14	return from a void function
E7	invalid operands	E15	statement not in loop/switch
E8	incorrect pointer/struct	OTH	Others

(a) Compiler Error Codes



(b) Compiler Errors Plot

Figure 3: Dataset Statistics. Tables 3a lists the various types of compilation errors encountered in our dataset of 23,275 single-line error programs. Figure 3b (note that its y-axis is in log-scale) charts the frequency of various error types in the entire dataset (blue) and the test set (red). The green plot (Compilation Success) depicts what number of errors of each type was TRACER able to successfully rectify in the test set, such that the resultant code compiles. The orange plot indicates how many times the top recommendation matches by TRACER were the exact target-abstraction fix expected by the student for that error. Despite this extremely stringent criterion, for most error types, TRACER has a success rate of more than 40%. Within its top 3 recommendations, TRACER corrects a much higher fraction 74% of errors across error types. TRACER excels at correcting challenging rare error types which have less than 200 instances in the *entire* dataset (E11: 78% correct, E12: 90% correct).

the correct source-target pairs were located at a distance of <= 1 from the line number reported in the compiler error message i.e. at, immediately above, or immediately below the compiler-reported line.

This suggests a surprisingly simple strategy for error localization: obtain a line number l from the compiler error message (recall that we are considering single-line edit programs for now) and simply consider the line numbers $l-1, l, l+1$ as candidate lines to attempt repair. This is the strategy adopted by TRACER for error localization.

What is more surprising is that this simple approach achieves almost the same error localization accuracy as much more involved techniques in literature. For instance, [7] utilize a deep network to perform error localization and report 87.5% accuracy in correctly including the location of the error in one of their top-5 predicted lines. TRACER achieves slightly higher accuracy using a technique that is much simpler.

3.2 Source and Target Abstraction

The second point of departure that TRACER makes from the state-of-the art is in *not* processing source and target lines in the form given in the student programs. Techniques such as recurrent neural networks operate with a static *vocabulary*.

As a result, supplying student programs directly to these networks requires all possible identifier/literal names possibly used by students to be included in the vocabulary which not only blows up the vocabulary size, but also creates problems for extending these approaches to newer offerings of the course where students may use hitherto unused identifier names and literals.

To remedy this problem, TRACER takes source-target line pairs and processes them by replacing all literals and identifier/variables with abstract tokens representing their corresponding types. The types are inferred using LLVM (the back-end for the Clang compiler suite) [12], a standard static analysis tool.

However, there are exceptions to the above rule. The names of keywords and some standard identifiers/library-functions such as {printf, scanf, malloc, NULL} are retained during abstraction. User defined function names are replaced by a generic token FUNC. A special token called INVALID is used for those literals and identifiers for which static analysis is unable to reveal the type.

The character/string literals are abstracted out to remove all text. Single/double quotes, as well as any format specifiers (such as {%d, %s, %f}) and character escape-sequences (such as {\n, \\}) are retained. For example, line number 5 in Figure 1 would be abstracted out as
printf("ans=%d", a+10); → printf("%d", INT+LITERAL_I);.

These exceptions to the abstraction rule exist since several errors made by students, especially in the initial days, involve the printf and scanf functions where it is crucial to retain the format string as is, to be able to identify and fix the error. For instance, for the programs in Figure 1, the source and target lines would be abstracted as follows

(1) (Source) scanf("%d",a); ⟶ scanf("%d",INT);
(2) (Target) scanf("%d",&a); ⟶ scanf("%d", & INT);

These abstracted lines are called respectively, the *Abstract Source Line* and the *Abstract Target Line*. For sake of simplicity, we will often refer to them as simply the *Source* and the *Target*. Table 1 lists several actual source and target pairs from our dataset.

We note that this technique of abstracting out literals is prevalent in literature. However, previous works such as [7] replace *all* identifiers/variables, including string-literals, with generic distinct tokens (an un-typed "ID_x"). Which precludes their ability to fix semantic-errors (which may be type-specific) and errors involving formatted strings (e.g. {printf,scanf} errors) which are very commonly faced by beginners. TRACER performs a much more nuanced abstraction that retains type-specific information that help it address a much wider range of errors.

3.3 Abstract Source-Target Line Translation

As mentioned before, TRACER performs repair by treating the abstract source and target lines as sequences of tokens and attempting to predict the target sequence using the source sequence. The tokens include reserved keywords such as {while, double}, standard library functions such as {printf, scanf} and abstract tokens such as {INT, FUNC, FLOAT} as discussed in the previous subsection. This sequence translation is performed using Recurrent Neural Networks (RNNs) which are described in detail in Section 4. In fact, for any source sequence, the RNN architecture is able to provide multiple suggestions for the target sequence.

This is beneficial in allowing a graceful degradation of the system. In our experiments, we observed that even if the top-ranked repair presented by the RNN is not the most appropriate, usually the second or the third ranked suggestions do often correspond to the most appropriate fix. TRACER uses a finely tuned encoder-decoder model with attention and long short-term memory mechanisms enabled. Details of parameter settings and tuning for our method are described in Section 5.

3.4 Target Recommendation and Concretization

TRACER offers recommended repairs in two formats – abstract and concrete (see Table 1). The abstract recommendations are obtained directly from the RNN framework by employing a beam search to obtain 5 target sequences with the highest scores. Note that these abstract sequences still contain tokens like {INT, FUNC, FLOAT}.

Now, the abstract recommendations may themselves be offered to students as hints and constitute valuable feedback. It may be argued that if given the actual corrected code, the student has no incentive to explore why did s/he make an error and what was the key to fixing the error. However, if only the abstract form of the repair/solution is provided as a hint, then the student is compelled to map the abstraction onto his/her own program which, in many cases, reveals what was the error in the source program, thus fulfilling several didactic goals.

However, TRACER goes one step further. Given recommended repairs in abstract form, TRACER can generate non-abstract versions of these repairs that can be applied to the original buggy program to produce code that actually compiles. This is done by performing *concretization*, a process which approximately reverses the abstraction step. We observe that our concretization technique is able to convert abstract versions of the target sequence to valid compilable code in 95% of cases in our dataset.

TRACER uses standard map-and-store based techniques to put back literals and function identifiers of appropriate type into the abstract recommendation to obtain a program that can be compiled. For this purpose, the Edlib tool [21] is used to compute the sequence alignment of the source-abstraction with recommended-abstraction (that is output by the RNN framework), based on edit distance. This sequence alignment is represented as a *cigar* string, a compact representation consisting of a chain of operators; primarily Match (=), Insert (I), Delete (D) or Mismatch/Replace (X).

Table 3: An example of the *concretization* process. The incorrect source line is xyz=4 where xyz has not been declared and a semi-colon is missing. TRACER correctly generates the abstract form of the repair INT = LITERAL_I;. However, multiple concretizations, all of whom produce valid compilable code, are possible. For example, if the identifiers i,j were declared as integer variables, then i=4; and j=4; are both valid concretizations.

source-line	xyz	=	4	
source-abstraction	INVALID	=	LITERAL_I	
recommended-abstraction	INT	=	LITERAL_I	;
Cigar (alignment path)	X	=	=	I
concrete-line	i	=	4	;

Each successful match with source-abstraction is replaced with corresponding concrete-code from (non-abstract) source-line. For mis-matches and inserts, TRACER replaces the recommended-abstract type with the closest concrete-code having the same type from the symbol table that is maintained by TRACER. An example of the concretization step is presented in Table 3.

3.5 Multiple Error Lines

Although the discussion so far has focused on programs where the fix is required on a single line, TRACER can be adapted to repair programs with errors present across multiple lines as well.

In our dataset, we observed that a large portion of programs having errors on multiple lines can be interpreted as simply multiple instances of single line errors, i.e. the errors in the multiple lines in these programs are not correlated and fixes may be applied to the lines individually. Hence, given a multi-line error program, TRACER does the following

1. **Error Localization**: TRACER fetches all the source-lines flagged by compiler for error, as well as the lines just above and just below those lines.
2. **Code Abstraction**: TRACER obtains source-abstractions for the above source-lines.
3. **Abstract Code Repair Prediction**: TRACER executes the RNN model on these source-abstractions to get the top-5 recommended-abstractions for each line.
4. **Concretization**: TRACER finally refines each of the recommended-abstractions to generate concrete, repaired code, and checks if the compiler error associated with that particular line disappears on applying the repair. If so, the concrete-code is retained as the fix for the corresponding source-line.

We consider a *multi-repair* done as outlined above to be successful only if all compiler errors are resolved as a result.

3.6 Performance Measures

We evaluate TRACER's performance with performance measures that are derived from those used in information retrieval, ranking, and recommendation systems. These are some of the most unforgiving performance measures and we are not aware of their prior

Table 4: Performance Metrics. TRACER uses some of the most stringent performance metrics to ensure that students receive recommendations that suggest fixes to correct the actual mistake they are making, and not merely remove compilation errors.

Performance Metric	Description
Prec@k, k ∈ {1 . . . 5}	Percentage of abstract source-target pairs where the top k abstract recommendations output by TRACER contain the abstract target line.
SPrec@k, k ∈ {1 . . . 5}	Percentage of abstract source-target pairs where the top k abstract recommendations output by TRACER contain any abstract target line which has the same abstract source line.

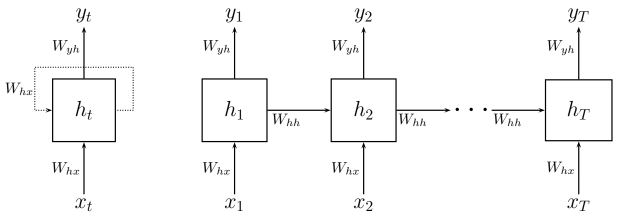


Figure 4: The schematic of a recurrent neural network

use in the program repair domain. The first performance measure we use is Precision at the Top (dubbed Prec@k). For every source-target pair, Prec@k gives a unit reward if the abstract target line is a part of the top k abstract recommendations returned by TRACER. Note that Prec@1 is an extremely stringent measure that accepts nothing but the exact solution expected by the student (in abstract form).

We also report performance on *Smoothed* Precision at the Top (SPrec@k). This performance measure takes into account the fact that upon abstraction, multiple source lines may map to the same abstract source line and consequently, that abstract source line may now map to multiple abstract target lines. Table 4 describes these performance measures.

4 RECURRENT NEURAL NETWORKS (RNN)

Recurrent neural networks (RNNs) have emerged as the learning model of choice in several areas that involve sequence modelling tasks such as natural language processing, speech recognition, image captioning etc. RNNs differ from classical neural networks in having an internal state and feedback loops into the network. The statefullness of the model and the ability to pass that state onto itself allow RNNs to effectively model sequences of data. Figure 4 shows the schematic of an RNN performing sequence translation.

Let $\{x_t\}, \{y_t\}$ etc denote strings over a shared alphabet Σ i.e. for all $t \geq 1$, we have $x_t, y_t \in \Sigma$. In their simplest form, RNNs are trained to learn a language model by predicting the next token in a sequence correctly. An output sequence $\{y_t\}$ is predicted as a function of the input sequence $\{x_t\}$. More specifically, after observing $\{x_1, x_2, \ldots, x_{t-1}\}$, the RNN predicts a token y_t. The RNN is trained to ensure that $y_t = x_t$.

In order to perform this prediction, the RNN maintains an internal state $h_t \in H$ that also evolves over time. Usually $H \subset \mathbb{R}^k$ is a set of real vectors of dimensionality k. Let the size of the vocabulary be $|\Sigma| = S$. Each token in $x \in \Sigma$ is represented as a d-dimensional vector (which we also denote as x by abusing notation). This representation is usually learned as well using techniques such as Word-to-Vec etc.

The prediction is made as a function of the hidden state and the hidden state itself evolves as a function of the previous hidden state and the current input as follows:

$$h_t = f_H(W_{hx}x_t + W_{hh}h_{t-1})$$
$$y_t = \text{SELECT}(f_O(W_{yh}^\top h_t)),$$

where f_O, f_H encode *activation* functions that map reals to reals (when applied to vectors, the activation functions act in a coordinate-wise manner) and $W_{yh} \in \mathbb{R}^{S\times k}, W_{hh} \in \mathbb{R}^{k\times k}, W_{hx} \in \mathbb{R}^{k\times d}$ are matrices. The SELECT operation simply chooses the coordinate of a vector with the largest value. Since $f_O(W_{yh}^\top h_t)$ is a $S = |\Sigma|$-dimensional vector, the SELECT operation returns a token in Σ.

Unequal Sequence Lengths: A specific hurdle that we face while using RNNs for program repair is that of input and output sequences being of unequal length. This can arise due to the fix in the incorrect program requiring insertions and/or deletions of tokens (for example, see Figures 1 and 2). The Encoder-decoder model [4, 10, 22] is a generic solution to this problem that employs two components, an encoder and a decoder. The encoder operates by using the input sequence to generate a sequence of hidden states.

$$h_t = f_H(W_{hx}x_t + W_{hh}h_{t-1})$$

At the end of the sequence, an intermediate representation, known as the *context vector* is computed as a function of the hidden state sequence $\{h_t\}$.

$$c = q(h_1, \ldots, h_T)$$

The decoder generates a fresh sequence of (still hidden) states $\{s_t\}$ using the context vector and previous hidden states. These states are used to generate an output sequence $\{y_t\}$

$$p(y_t|y_1, \ldots, y_{t-1}, c) = g_O(y_{t-1}, s_t, c)$$

until a special delimiter token $\langle \text{eos} \rangle$ is generated, indicating a termination of the output sequence.

Handling Long Sequences: A significant hurdle to training RNNs on long sequences, such as those we encounter in our program repair application, is the problem of vanishing or exploding gradients [18]. An elegant fix to this problem is the Long Short Term Memory (LSTM) model [9] and its variants which overcome the problem by replacing hidden states by a gating mechanism, which allows gradients to flow freely in the backpropagation-through-time algorithm.

The problem emerges in a different form when dealing with long output sequences where a single context vector becomes insufficient to predict an output sequence of arbitrary length. *Attention mechanisms* [1] overcome this problem by identifying for each output token y_t, a specific part of input sequence which is most relevant for predicting y_t. This is done by employing a separate context vector c_t for predicting the output token y_t instead of a uniform one. These context vectors are generated by a separate neural network that is trained jointly with the RNN. Typically a weighted combination of the hidden states of the encoder are used to generate these context vectors.

We regret our inability to describe RNN frameworks in greater detail due to lack of space and refer the reader to some excellent tutorials on RNNs [11], LSTMs [16], and attention mechanisms [3].

Usefulness of the Error Localization Step: Even with attention mechanisms, we found RNNs with Encoder-decoder models to struggle when trained on entire programs. This is because the decoder in such situations is heavily stressed to identify the relevant subset of the input sequence for every output token, something that makes performance go down, as well as training and prediction times to go up. However, the modular approach adopted by TRACER, that first identifies a very small (often 3) set of sentences to focus on, greatly improves the ability of the RNN framework to analyze and suggest relevant local fixes.

5 EXPERIMENTS

Experimental setup: All experiments were performed on a system with an Intel® Core™ i7 CPU 930 @ 2.80GHz × 8 CPU with 8GB RAM, and an NVIDIA GeForce® GTX 760 GPU with 2GB GPU Memory.
Dataset: Our dataset contained a total of 16985 (source, target) line pairs, which were further divided into training (70%), validation(10%) and test(20%) sets. Validation and test examples were randomly picked from the dataset. The most frequent 150 and 140 tokens were chosen for the source and target vocabulary, respectively for training the RNN i.e. $|\Sigma| = 150$ for the input vocabulary and 140 for the output vocabulary. Tokens not in vocabulary were replaced by a special token UNK. The maximum length of source and target sequences was set to 80 and 82, respectively.
Training: We trained a supervised Encoder-Decoder model with attention mechanism on an open source Torch implementation of a standard sequence-to-sequence model with (optional) attention mechanism where the encoder-decoder are LSTMs[1]. The models were trained by minimizing the class negative likelihood loss. We conducted an extensive grid search to set hyperparameters: number of hidden layers for both Encoder and Decoder in $\{1, 2, 3, 4\}$, size of the LSTM hidden state in $\{50, 100, 200, 250, 300, 350\}$, and word embedding size in $\{50, 100, 150, 200, 250, 300\}$. Word embeddings were learnt jointly with network parameters. We tried both unidirectional and bidirectional RNNs with reverse source side setting. Apart from this, we used a mini-batch size of 32 for training, standard stochastic gradient descent with an initial learning rate 1 and learning rate decay of 0.5 after the 9-th epoch for a total of 35 epochs. The above configurations were found to be the best among those permitted by our server resources, upon cross validation. We initialized the hidden state of the Decoder at time 0 with last hidden state of the Encoder, initialized other parameters randomly in range $[-0.1, 0.1]$, clipped gradients at magnitude 5, and used a dropout probability of 0.3 between LSTM layers. The best model based on validation perplexity was found to be a bidirectional Encoder with 2 hidden layers, a hidden state size of $k = 300$, word embedding size $d = 100$. Reversing the source sequence gave poor results.
Prediction: We performed a beam search with beam size 50 to select the best 20 target sequences. Out of these 20 the top 5 unique predictions were used for measuring performance according to the measures described in Section 3.6.

Table 5: Prediction Accuracy of TRACER on compilation-error repair experiments. TRACER excels on the challenging Prec@k and SPrec@k metrics.

k	Prec@k	SPrec@k
1	59.6	68.61
2	64.9	72.73
3	66.61	73.85
4	67.85	74.73
5	68.32	75.15

5.1 Results

We note that we performed these experiments in cross validation mode with 5 random train-validation-test splits of the data as well and found results to be very similar to those we report below.

The prediction accuracies of TRACER on a test set of 4,578 programs are reported in Table-5. TRACER is able to correctly predict the exact abstraction as the student target repair as its top suggestion in 59.6% of the instances. If we include the top 3 recommendations of TRACER, then this figure jumps to 66.6% for Prec@3 and further to 73.85% for SPrec@3.

Figure-3b shows that TRACER consistently achieves high levels of Prec@1 accuracy in predicting the exact student repair, irrespective of the type of compiler error. It fails on just two error types, namely *E7: too few args to function call* and *E13: too many args to function call*. This is because presently, TRACER cannot predict the correct number of parameters for a function call in the *target*. We have developed extensions of TRACER that seek to correct this limitation which will appear in future reports.

Table-1 lists a few interesting examples from our dataset on which TRACER was able to provide correct and relevant fixes. For the first two examples, TRACER makes an accurate prediction at the very top, correctly suggesting the insertion of an arithmetic operator in example #1 and switching the L and R values in example #2. For the rest of the examples, its top recommendation does not match the student fix. However, notice that TRACER's top fix is still an appropriate fix.

In examples #4 and #5, TRACER predicts an abstract fix which is semantically equivalent to the desired fix but we nevertheless penalize it due to our stringent evaluation criteria of an exact match with the student repair. TRACER arguably produces a simpler fix than what the student devised for examples #4 and #5. TRACER is able to improve upon any individual student's fixes since it learns from frequent patterns from other student submissions as well.

The most interesting case is example #3 where the student's submission, though syntactically correct, results in a compiler warning *incompatible integer to pointer conversion passing 'int' to parameter*

[1] https://github.com/harvardnlp/seq2seq-attn

*of type 'const char *'*. TRACER's suggestion is better since it does not generate any compiler warning, and is doing what is intended. However, our evaluation metrics still consider it a failure due to the mismatch with the student repair.

In future, we plan to develop better scoring mechanisms to evaluate our predictions. Nonetheless, even with such stringent metrics, TRACER is able to achieve high accuracy of 59.6 % for Prec@1. TRACER is unable to incorporate global context while suggesting fixes. For example, in example #6, TRACER produces the *source* verbatim since it is unable to figure out the desired number of opening braces from the local context. In future, we plan to incorporate global context as well to predict such fixes.

5.2 End-to-End Repair

In Figure 5, we demonstrate the overall end-to-end accuracy of TRACER on our dataset of single-line errors, across all the labs. The *Abstraction_Match* legend denotes how many times our recommended-abstraction matched the *exact* target-abstraction (the abstraction of fix performed by same student). *Concrete_Compile* denotes what % of the erroneous programs was TRACER able to repair and compile.

Table 6 reports the compilation success rates of the multiple-error approach outlined in Section 3.5 on our single-line (errors requiring fix at a single line), multiple-line (errors requiring fix at multiple different lines), and on the dataset obtained from DeepFix[2] [7].

TRACER is able to fix 79.27% of the programs on our testing set of single-line edit program pairs (referred to as Single_Test), while being highly relevant at the same time (as demonstrated in Table 5). TRACER is also able to successfully repair about 44% of programs with multiple-line errors obtained from our course (denoted as "Multiple" in Table 6) and on the collection of programs used in DeepFix [7]. Note that DeepFix, the current state-of-the-art was able to achieve only 27% compilation success rate on the same set of programs.

Invoking the deep-network takes the maximum amount of time in this entire setup, while abstraction/concretization and compilation steps take an order of milli-seconds time on average. Hence to ameliorate this, we cache the frequently looked-up abstraction translations during training phase. This reduces the time taken for the entire repair process to just 1.66 seconds on average per erroneous program, during the testing phase.

6 RELATED WORK

To the best of our knowledge, TRACER is the first approach to perform targeted repair where we learn and predict the exact fix for a given bug, instead of predicting it as a side-effect of not matching with a generic correct grammar. Prior works [2, 7, 19] learn repairs by observing generic correct programs, but do not have a well defined criterion to evaluate the quality of the repairs. For example, simply deleting the erroneous line makes the error go away in a non-trivial fraction of buggy programs, but this may not be an acceptable fix.

Table 6: Overall accuracy of TRACER on three different datasets. Single_Test is the test set on single-line edit program pairs. Multiple is the set of programs requiring repairs on multiple lines. DeepFix is the dataset used by [7]. On all datasets TRACER gives compilable code on a large fraction of programs. On the DeepFix dataset, the method of [7] itself offers only 27% compilation success whereas TRACER offers a much higher 44% success rate.

Dataset	#Programs	#Compiler-Errors	TRACER Repair %
Single_Test	4,578	4,853	79.27
Multiple	17,451	24,255	43.67
DeepFix	6,971	16,743	43.97

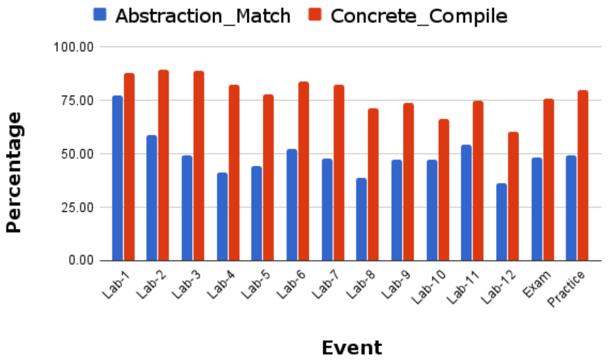


Figure 5: Overall accuracy of TRACER, shown per lab. TRACER is robust to handle compiler errors occurring across all labs. Even on erroneous programs dealing with advanced concepts such as pointers and recursion, TRACER is able to consistently achieve high repair rate.

The approach used by DeepFix [7] to repair common C programming errors comes closest to our work. DeepFix learns a seq2seq Neural Network on the entire program, and features an error localization module which, with the help of an Oracle, can attempt to resolve multi-line errors by making multiple passes. TRACER on the other hand focuses on single-line errors and achieves a high compilation accuracy, while being highly relevant to the student target. In fact on the very dataset used by [7], TRACER offers significantly higher compilation success rates than Deepfix itself.

HelpMeOut [8] gives relevant examples of solutions for a compilation error by searching a database for the same error encountered by other students. It provides both the erroneous line of the other student, as reported by compiler, as well as the modified line which resulted in successful compilation. However, unlike TRACER, the repair is picked from a database and is not tuned to the erroneous source program. Moreover, the approach provides the student the fix directly, which can be suboptimal in terms of learning outcomes. TRACER instead learns the repair from the submissions of the other students, and suggests the exact abstract/concrete fix tuned for the erroneous source program.

Recent studies [25] have indicated that program repairs can also be used by human graders, who are experienced programmers, to decrease the amount of grading time. The positive impact of

[2] https://www.cse.iitk.ac.in/users/karkare/prutor/prutor-deepfix-09-12-2017.db.gz

compilation error repairs on (automated) grading is also reported by *GradeIT* [17] that uses simple rewrite rules to repair compilation errors. The repairs generated by TRACER can further improve the performance of systems such as *GradeIT*.

7 FUTURE WORK

Our experiments confirm that TRACER performs very well on errors where repair can typically be obtained by looking at a local context, for example, inserting a token or restructuring an expression. However, TRACER does not yet take into account the global context, e.g. the number of parameters of a function defined away from its call, opening/closing a missing brace, undeclared variables etc. Some of these global context errors occur in the most frequent list and can be handled by a separate technique which runs in tandem with TRACER. Future versions of TRACER are planned to have these features to widen its scope.

Also, our evaluation metrics currently do not discount minor syntactic variations, e.g. `{a != b}` vs `{!(a == b)}`, while computing the mismatch between tool repair and the student repair. We believe a more moderate performance measure will give us a more realistic picture of the performance of TRACER and other such error-correction tools. Finally, it is worthwhile to combine TRACER with semantic repair tools such as Prophet [13] to further refine the repairs. TRACER is currently being deployed on a live offering of the C programming course and a study investigating its effects on student experience will be released soon.

8 CONCLUSION

We presented TRACER, a tool to generate targeted repairs aimed at novice programmers. TRACER offers extremely accurate recommendations for fixes and on more than 4000 test programs with single-line errors, its top three recommendations include the correct repair 74% of the time. Even on more than 17000 programs with errors on multiple lines, TRACER offers a compilation success rate of more than 40%. TRACER takes only several milliseconds to make its recommendations, making it suitable for live deployment. Although we focused on the C programming language in this paper, TRACER can be easily ported to other programming languages such as C++, Java, etc. Given enough data, TRACER can also be used predict fixes for compilation errors in the programs in future offerings of a course. TRACER's performance on stringent correctness criterion strengthens our claim that repairs suggested by it are close to the fixes performed by the students themselves. As a result, these repairs are of more didactic value than the compiler produced error messages or repairs that aim to only remove compile-time errors. High accuracy and student-friendliness of the repairs generated by TRACER make it an attractive virtual teaching assistant for programming courses offered at a massive scale.

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