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DeepMerge: Learning to Merge Programs

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Abstract—In collaborative software development, program merging is *the* mechanism to integrate changes from multiple programmers. Merge algorithms in modern version control systems report a conflict when changes interfere textually. Merge conflicts require manual intervention and frequently stall modern continuous integration pipelines. Prior work found that, although costly, a large majority of resolutions involve re-arranging text without writing any new code. Inspired by this observation we propose the *first data-driven approach* to resolve merge conflicts with a machine learning model. We realize our approach in a tool DEEPMERGE that uses a novel combination of (i) an edit-aware embedding of merge inputs and (ii) a variation of pointer networks, to construct resolutions from input segments. We also propose an algorithm to localize manual resolutions in a resolved file and employ it to curate a ground-truth dataset comprising 8,719 non-trivial resolutions in JavaScript programs. Our evaluation shows that, on a held out test set, DEEPMERGE can predict correct resolutions for 37% of non-trivial merges, compared to only 4% by a state-of-the-art semistructured merge technique. Furthermore, on the subset of merges with upto 3 lines (comprising 24% of the total dataset), DEEPMERGE can predict correct resolutions with 78% accuracy.

1 INTRODUCTION

In collaborative software development settings, version control systems such as "git" are commonplace. Such version control systems allow developers to simultaneously edit code through features called branches. Branches are a growing trend in version control as they allow developers to work in their own isolated workspace, making changes independently, and only integrating their work into the main line of development when it is complete. Integrating these changes frequently involves merging multiple copies of the source code. In fact, according to a large-scale empirical study of Java projects on GitHub [13], nearly 12% of all commits are related to a merge.

To integrate changes by multiple developers across branches, version control systems utilize merge algorithms. Textual three-way file merge (e.g. present in *"git merge"*) is the prevailing merge algorithm. As the name suggests, three-way merge takes three files as input: the common *base* file $\mathcal{O}$, and its corresponding modified files, $\mathcal{A}$ and $\mathcal{B}$. The algorithm either:

1) declares a "conflict" if the two changes interfere with each other, or
2) provides a merged file $\mathcal{M}$ that incorporates changes made in $\mathcal{A}$ and $\mathcal{B}$.

Under the hood, three-way merge typically employs the `diff3` algorithm, which performs an *unstructured* (line-based) merge [36]. Intuitively, the algorithm *aligns* the two-way diffs of $\mathcal{A}$ (resp. $\mathcal{B}$) over the common base $\mathcal{O}$ into a sequence of diff slots. At each slot, a change from either $\mathcal{A}$ or $\mathcal{B}$ is incorporated. If both programs change a common slot, a *merge conflict* is produced, and requires manual resolution of the conflicting modifications.

	Base $\mathcal{O}$ (`base.js`)	Variant $\mathcal{A}$ (`a.js`)	Variant $\mathcal{B}$ (`b.js`)	Resolution? (`m.js`)

(1).	`y = 42;`	`x = 1;`
		`y = 42;`
			`y = 42;`
			`z = 43;`
				`x = 1;`
				`y = 42;`
				`z = 43;`

(2).	`y = 42;`	`x = 1;` `y = 42;`	`z = 43;` `y = 42;`	`CONFLICT`

Figure 1: Two examples of unstructured merges.

Figure 1 shows two simple code snippets to illustrate examples of three-way merge inputs and outputs. The figure shows the base program file $\mathcal{O}$ along with the two variants $\mathcal{A}$ and $\mathcal{B}$. Example (1) shows a case where `diff3` successfully provides a merged file $\mathcal{M}$ incorporating changes made in both $\mathcal{A}$ and $\mathcal{B}$. On the other hand, Example (2) shows a case where `diff3` declares a conflict because two independent changes (updates to `x` and `z`) occur in the same diff slot.

When `diff3` declares a conflict, a developer must intervene. Consequently, merge conflicts are consistently ranked as one of the most taxing issues in collaborative, open-source software development, "especially for seemingly less experienced developers" [15]. Merge conflicts impact developer productivity, resulting in costly broken builds that stall the continuous integration (CI) pipelines for several hours to days. The fraction of merge conflicts as a percentage of merges range from 10% — 20% for most collaborative projects. In several large projects, merge conflicts account for up to 50% of merges (see [13] for details of prior studies).

Merge conflicts often arise due to the unstructured `diff3` algorithm that simply checks if two changes occur in the same diff slot. For instance, the changes in Example (2), although textually conflicting, do not interfere semantically. This insight has inspired research to incorporate program structure and semantics while performing a merge. *Structured merge* approaches [3], [25], [42] and their variants treat merge inputs as abstract syntax trees (ASTs), and use tree-structured merge algorithms. However, such approaches still yield a conflict on merges such as Example (2) above, as

```
{ unchanged lines (prefix) }
<<<<<<
{ lines edited by 𝒜 }
|||||||
{ affected lines of base 𝒪 }
=======
{ lines edited by ℬ }
>>>>>>
{ unchanged lines (suffix) }
```

(a) Format of a conflict.

```
<<<<<< a.js
x = 1;
|||||| base.js
=======
z = 43;
>>>>>> b.js
y = 42;
```

(b) Instance of a conflict.

Figure 2: Conflict format and an instance reported by `diff3` on Example (2) from Figure 1.

they do not model program semantics and cannot safely reorder statements that have side effects.[1] To make matters worse, the gains from structured approaches hardly transfer to dynamic languages, namely JavaScript [42], due to the absence of static types. Semantics-based approaches [47], [37] can, in theory, employ program analysis and verifiers to detect and synthesize the resolutions. However, there are no semantics-based tools for synthesizing merges for any real-world programming language, reflecting the intractable nature of the problem. Current automatic approaches fall short, suggesting that merge conflict resolution is a non-trivial problem.

This paper takes a *fresh data-driven* approach to the problem of resolving unstructured merge conflicts. Inspired by the abundance of data in open-source projects, the paper demonstrates how to collect a dataset of merge conflicts and resolutions.

This dataset drives the paper's key insight: a vast majority (80%) of resolutions do not introduce new lines. Instead, they consist of (potentially rearranged) lines from the conflict region. This observation is related to the "plastic surgery hypothesis" [5] and the "redundancy assumption[2]" [28] and is confirmed by a prior independent large-scale study of Java projects from GitHub [15], in which 87% of resolutions are comprised exclusively from lines in the input. In other words, a typical resolution consists of re-arranging conflicting lines without writing any new code. Our observation naturally begs the question: *Are there latent patterns of rearrangement? Can these patterns be learned?*

This paper investigates the potential for learning latent patterns of rearrangement. Effectively, this boils down to the question:

Can we learn to synthesize merge conflict resolutions?

Specifically, the paper frames merging as a sequence-to-sequence task akin to machine translation.

To formulate program merging as a sequence-to-sequence problem, the paper considers the text of programs $\mathcal{A}$, $\mathcal{B}$, and $\mathcal{O}$ as the input sequence, and the text of the resolved program $\mathcal{M}$ as the output sequence. However, this seemingly simple formulation does not come without challenges. Section 5 demonstrates an out of the box sequence-to-sequence model trained on merge conflicts yields very low accuracy. In order to effectively learn a merge algorithm, one must:

1) represent merge inputs in a concise yet sufficiently expressive sequence;
2) create a mechanism to output tokens at the line granularity; and
3) localize the merge conflicts and the resolutions in a given file.

To represent the input in a concise yet expressive embedding, the paper shows how to construct an edit aware sequence to be consumed by DEEPMERGE. These edits are provided in the format of `diff3` which is depicted in Figure 2(a) in the portion between markers "<<<<<<<" and ">>>>>>>". The input embedding is extracted from parsing the conflicting markers and represents $\mathcal{A}$'s and $\mathcal{B}$'s edits over the common base $\mathcal{O}$. In this paper we refer to the lines of code between the conflict start marker (<<<<<<<) and the conflict end marker (>>>>>>>) as a *conflict region*.

To represent the output at the line granularity, DEEPMERGE's design is a form of a pointer network [44]. As such, DEEPMERGE constructs resolutions by copying input lines, rather than learning to generate them token by token. Guided by our key insight that a large majority of resolutions are entirely comprised of lines from the input, such an output vocabulary is sufficiently expressive.

Lastly, the paper shows how to localize merge conflicts and the corresponding user resolutions in a given file. This is necessary as our approach exclusively aims to resolve locations in which `diff3` has declared a conflict. As such, our algorithm only needs to generate the conflict resolution and not the entire merged file. Thus, to extract ground truth, we must localize the resolution for a given conflict in a resolved file. Localizing such a resolution region unambiguously is a non-trivial task. The presence of extraneous changes unrelated to conflict resolution makes resolution localization challenging. The paper presents the first algorithm to localize the resolution region for a conflict. This ground truth is essential for training such a deep learning model.

The paper demonstrates an instance of DEEPMERGE trained to resolve unstructured merge conflicts in JavaScript programs. Besides its popularity, JavaScript is notorious for its rich dynamic features, and lacks tooling support. Existing structured approaches struggle with JavaScript [42], providing a strong motivation for a technique suitable for dynamic languages. The paper contributes a real-world dataset of 8,719 merge tuples that require non-trivial resolutions from nearly twenty thousand repositories in GitHub. Our evaluation shows that, on a held out test set, DEEPMERGE can predict correct resolutions for 37% of non-trivial merges. DEEPMERGE's accuracy is a 9x improvement over a recent semistructured approach [42], evaluated on the same dataset. Furthermore, on the subset of merges with upto 3 lines (comprising 24% of the total dataset), DEEPMERGE can predict correct resolutions with 78% accuracy.

Contributions. In summary, this paper:

1) is the first to define merge conflict resolution as a machine learning problem and identify a set of challenges for encoding it as a sequence-to-sequence supervised learning problem (§ 2).
2) presents a data-driven merge tool DEEPMERGE that uses edit-aware embedding to represent merge inputs and a variation of pointer networks to construct the resolved program (§ 3).

1. We ran `jdime` [25] in `structured` mode on this example after translating the code snippet to Java.

2. Please see section 8 for an in depth discussion of how the Plastic Surgery Hypothesis and the Redundancy Assumption relate to this work.

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3) derives a real-world merge datasetfor supervised learning by proposing an algorithm for localizing resolution regions (§ 4).
4) performs an extensive evaluation of DEEPMERGE on merge conflicts in real-world JavaScript programs. And, demonstrates that it can correctly resolve a significant fraction of unstructured merge conflicts with high precision and 9x higher accuracy than a structured approach.

2 DATA-DRIVEN MERGE

We formulate program merging as a sequence-to-sequence supervised learning problem and discuss the challenges we must address in solving the resulting formulation.

2.1 Problem Formulation

A merge consists of a 4-tuple of programs $(\mathcal{A}, \mathcal{B}, \mathcal{O}, \mathcal{M})$ where $\mathcal{A}$ and $\mathcal{B}$ are both derived from a common $\mathcal{O}$, and $\mathcal{M}$ is the developer resolved program.

A merge may consist of one or more regions. We define a *merge tuple* $((A, B, O), R)$ such that A, B, O are (sub) programs that correspond to regions in $\mathcal{A}$, $\mathcal{B}$, and $\mathcal{O}$, respectively, and R denotes the result of merging those regions. Although we refer to (A, B, O, R) as a merge tuple, we assume that the tuples also implicitly contain the programs that they came from as additional contexts (namely $\mathcal{A}, \mathcal{B}, \mathcal{O}, \mathcal{M}$).

Definition 1 (Data-driven Merge). Given a dataset of M merge tuples,

$$D = \{(A^i, B^i, O^i, R^i)\}_{i=1}^{M}$$

a data-driven merge algorithm *merge* is a function that maximizes:

$$\sum_{i=1}^{M} \mathit{merge}(A^i, B^i, O^i) = R^i$$

treating Boolean outcomes of the equality comparison as integer constants 1 (for `true`) and 0 (for `false`).

In other words, *merge* aims to maximize the number of merges from D. Rather than constraining merge to exactly satisfy *all* merge tuples in D, we relax the objective to maximization. A perfectly satisfying merge function may not exist in the presence of a real-world *noisy* dataset D. For instance, there may be $(A^i, B^i, O^i, R^i) \in D$ and $(A^j, B^j, O^j, R^j) \in D$ for $i \neq j$, $A^i = A^j$, $B^i = B^j$, $O^i = O^j$ but $R^i \neq R^j$. In other words, two merge tuples consist of the same edits but different resolutions.

Example 1. Figure 3(a) shows a merge instance that we will use as our running example throughout. This instance is formulated in our setting as the merge tuple (A, B, O, R) depicted in Figure 3(b). R contains only lines occurring in the input. The two lines in R correspond to the first line of B and the third line of A. For this example, the R also incorporates the intents from both A and B intuitively, assuming `b` does not appear in the rest of the programs. □

One possible way to learn a *merge* algorithm is by modeling the conditional probability

$$p(R|A, B, O) \tag{1}$$

In other words, a model that copies and orders portions of the input programs to produce the output program R.

```
<<<<<<< a.js
let b = x + 5.7
var y = floor(b)
console.log(y)
||||||| base.js
var b = 5.7
var y = floor(b)
=======
var y = floor(x + 5.7)
>>>>>>> b.js
```

(a) A merge instance.

A =
```
let b = x + 5.7
var y = floor(b)
console.log(y)
```

O =
```
var b = 5.7
var y = floor(b)
```

B =
```
var y = floor(x + 5.7)
```

R =
```
var y = floor(x + 5.7)
console.log(y)
```

(b) Corresponding merge tuple.

Figure 3: Formulation of a merge instance in our setting.

Because programs are sequences, we further decompose Eq 1 by applying the chain rule [38]:

$$p(R|A, B, O) = \prod_{j=1}^{N} p(R_j | R_{<j}, A, B, O)$$

This models the probability of copying an element from A, B, or O into the $j-$th element of the R, given the elements copied into R so far. There are many possible ways to model a three-way merge. However, the above formulation suggests one obvious approach is to use a maximum likelihood estimate of a sequence-to-sequence model.

2.2 Challenges

Applying a sequence-to-sequence (Seq2seq) model to merge conflict resolution poses unique challenges. We discuss three key challenges, concerning input representation, output construction, and dataset extraction.

2.2.1 Representing the Merge Inputs as a Sequence.

In a traditional sequence-to-sequence task such as machine translation, there is a single input sequence that maps to a single output sequence. However, in our case, we have three input sequences of varying sizes, corresponding to the three versions of a program involved in a merge conflict. It is not immediately evident how to determine a suitable token granularity and encode these sequences in a manner that is amenable to learning. One obvious solution is to concatenate the tokens of the three sequences to obtain a single sequence. However, the order of concatenation is unclear. Furthermore, as we show in Section 3.2, such a naive representation not only suffers from information loss and truncation, but also poor precision by being unaware of A and B's edits over common base O. In summary, we have:

CH1: *Encode programs A, B, and O as the input to a Seq2Seq model.*

2.2.2 Constructing the Output Resolution

Our key insight that a majority of resolutions do not introduce new lines leads us to construct the output resolution directly from lines in the conflict region. This naturally suggests the use of pointer networks [44], an encoder-decoder architecture capable of producing outputs explicitly pointing to tokens in the input sequence. However, a pointer network formulation suggests an equivalent input and output granularity. In Section 3.2, we show that the input is best represented at a granularity far smaller than lines.

Thus, the challenge is:

CH2: *Output R at the line granularity given a non-line granularity input.*

2.2.3 Extracting Ground Truth from Raw Merge Data.

Finally, to learn a data-driven merge algorithm, we need real-world data that serves as ground truth. Creating this dataset poses non-trivial challenges. First, we need to localize the resolution region and corresponding conflict region. In some cases, developers performing a manual merge resolution made changes unrelated to the merge. Localizing resolution regions unambiguously from input programs is challenging due to the presence of these unrelated changes. Second, we need to be able to recognize and subsequently filter merge resolutions that only include changes from one side of the merge but completely ignore the changes in the other. One behavior of developers faced with a merge conflict is to simply use the version in one of the incoming branches as the resolution and later incorporate the changes from the other branch. In these cases, the version of the file checked in at the merge point in the repository does not accurately represent the "correct" merge resolution and should not be used. In summary, we have:

CH3: *Identify merge tuples $\{(A^i, B^i, O^i, R^i)\}_{i=1}^{M}$ given $(\mathcal{A}, \mathcal{B}, \mathcal{O}, \mathcal{M})$.*

3 The DeepMerge Architecture

Section 2 suggested one way to learn a three-way merge is through a maximum likelihood estimate of a sequence-to-sequence model. In this section we describe DeepMerge, the first data-driven merge framework, and discuss how it addresses challenges **CH1** and **CH2**. We motivate the design of DeepMerge by comparing it to a standard sequence-to-sequence model, the encoder-decoder architecture.

3.1 Encoder Decoder Architectures

Sequence-to-sequence models aim to map a fixed-length input ($(X_N)_{N\in\mathbb{N}}$), to a fixed-length output, ($(Y_M)_{M\in\mathbb{N}}$) [39]. [3] The standard sequence-to-sequence model consists of three components: an **input embedding**, an **encoder**, and a **decoder**.

Input embedding: An embedding maps a discrete input from an input vocabulary V ($x_n \in \mathbb{N}^{|V|}$), to a continuous D dimensional vector space representation ($\overline{x}_n \in \mathbb{R}^D$) [30]. Such a mapping is obtained by multiplication over an embedding matrix $E \in \mathbb{R}^{D\times|V|}$. Applying this for each element of X_N gives $\overline{X}_N$.

Encoder: An encoder *encode*, processes each $\overline{x}_n$ and produces a hidden state, z_n which summarizes the sequence upto the n-th element. At each iteration, the encoder takes as input the current sequence element x_n, and the previous hidden state z_{n-1}. After processing the entire input sequence, the final hidden state, z_N, is passed to the decoder.

3. Note that M is not necessary equal to N.

Decoder: A decoder *decode*, produces the output sequence Y_M from an encoder hidden state Z_n. Similar to encoders, decoders work in an iterative fashion. At each iteration, the decoder produces a single output token y_m along with a hidden summarization state h_m. The current hidden state and the previous predicted token y_m are then used in the following iteration to produce y_{m+1} and h_{m+1}. Each y_m the model predicts is selected through a softmax over the hidden state:

$$p(y_m|y_1, ..., y_{m-1}, X) = \textit{softmax}(h_m)$$

DeepMerge is based on this encoder-decoder architecture with two significant differences.

First, rather than a standard embedding followed by encoder, we introduce a novel embedding method called *Merge2Matrix*. *Merge2Matrix* addresses **CH1** by summarizing input programs (A, B, O) into a single embedding fed to the encoder. We discuss our *Merge2Matrix* solution as well as less effective alternatives in Section 3.2.

Second, rather than using a standard decoder to generate output tokens in some output token vocabulary, we augment the decoder to function as a variant of pointer networks. The decoder outputs line tuples (i, W) where $W \in \{A, B\}$ and i is the i-th line in W. We discuss this in detail in Section 3.4.

Example 2. Figure 4 illustrates the flow of DeepMerge as it processes the inputs of a merge tuple. First, the raw text of A, B, and O is fed to *Merge2Matrix*. As the name suggests, *Merge2Matrix* summarizes the tokenized inputs as a matrix. That matrix is then fed to an encoder which computes the encoder hidden state z_N. Along with the start token for the decoder hidden state, the decoder takes z_N and iteratively (denoted by the $\cdots$) generates as output the lines to copy from A and B. The final resolution is shown in the green box. □

3.2 *Merge2Matrix*

An encoder takes a single sequence as input. As discussed in Section 2.2, a merge tuple consists of three sequences. This section introduces *Merge2Matrix*, an input representation that expresses the tuple as a single sequence. It consists of embedding, transformations to summarize embeddings, and finally, edit-aware alignment.

3.2.1 Tokenization and Embedding

This section discusses our relatively straightforward application of both tokenization and embedding.

Tokenization. Working with textual data requires tokenization whereby we split a sequence of text into smaller units referred to as *tokens*. Tokens can be defined at varying granularities such as characters, words, or sub-words. These units form a *vocabulary* which maps input tokens to integer indices. Thus, a vocabulary is a mapping from a sequence of text to a sequence of integers. This paper uses byte-pair encoding (BPE) as it has been shown to work well with source code, where tokens can be formed by combining different words via casing conventions (e.g. `snake_case` or `camelCase`) causing a blowup in vocabulary size [22]. Byte-pair encoding is an unsupervised sub-word tokenization

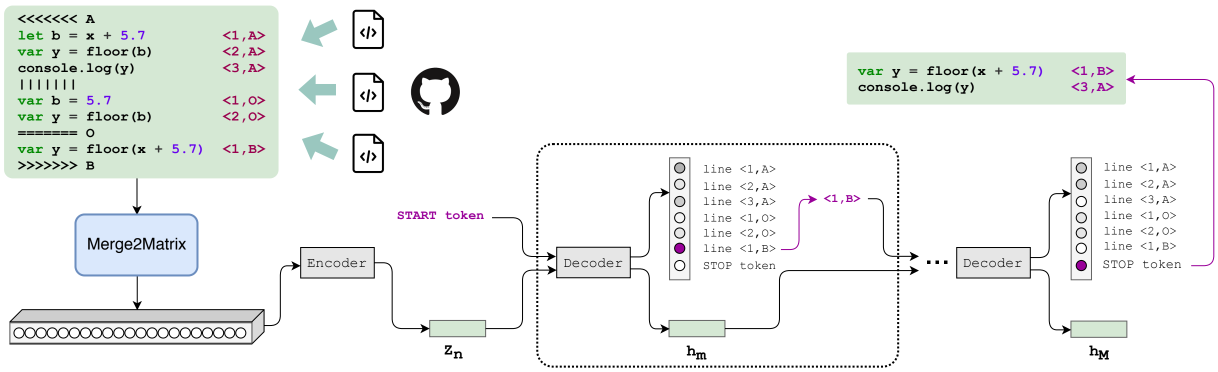

Figure 4: Overall DEEPMERGE framework. The dotted box represents repetition of *decode* until $m = M$ i.e. the $\langle \texttt{STOP} \rangle$ token is predicted. In this example, we have omitted $m = 2$ in which the call to *decode* outputs $y_2 = \langle 3, A \rangle$.

that draws inspiration from information theory and data compression wherein frequently occurring sub-word pairs are recursively merged and stored in the vocabulary. We found that the quality of results when using BPE was empirically superior to the results when using other tokenization schemes.

Embedding. Given an input sequence X_N, and a hyperparameter (embedding dimension) D, an embedding transformation creates $\overline{X}_N$. As described in Section 3.1, the output of this embedding is then fed to an encoder. Because a merge tuple consists of three inputs (A, B, and O), the following sections introduce novel transformations that *summarize* these three inputs into a format suitable for the encoder.

3.2.2 Merge Tuple Summarization

In this section, we describe summarization techniques that are employed after embedding. Before we delve into details, we first introduce two functions used in summarization.

Suppose a function that concatenates embedded representations:

$$concat_s : (\mathbb{R}^{D\times N} \times \cdots \times \mathbb{R}^{D\times N}) \to \mathbb{R}^{D\times sN}$$

that takes s similarly shaped tensors as arguments and concatenates them along their last dimension. Concatenating these s embeddings increases the size of the encoder's input by a factor of s.

Suppose a function $linearize$ that linearly combines s embedded representations. We parameterize this function with learnable parameters $\theta \in \mathbb{R}^{s+1}$. As input, $linearize$ takes an embedding $\overline{x}_i \in \mathbb{R}^D$ for $i \in 1..S$. Thus, we define

$$linearize_\theta(\overline{x}_1, \ldots, \overline{x}_s) = \theta_1 \cdot \overline{x}_1 + \cdots + \theta_s \cdot \overline{x}_s + \theta_{s+1}$$

where all operations on the inputs $\overline{x}_1, \ldots, \overline{x}_s$ are pointwise. $linearize$ reduces the size of the embeddings fed to the encoder by a factor of s.

Now that we have defined two helper functions, we describe two summarization methods.

Naïve. Given a merge tuple's inputs (A, B, O), a *naïve* implementation of *Merge2Matrix* is to simply concatenate the embedded representations (i.e., $concat_3(\overline{A}, \overline{B}, \overline{O})$) Traditional sequence-to-sequence models often suffer from information forgetting; as the input grows longer, it becomes harder for *encode* to capture long-range correlations in that input. A solution that addresses **CH1**, must be concise while retaining the information in the input programs.

Linearized. As an attempt at a more concise representation, we introduce a summarization we call *linearized*. This method linearly combines each of the embeddings through our helper function: $linearize_\theta(\overline{A}, \overline{B}, \overline{O})$. $linearize_\theta$ is related to attention, but encapsulates more than just attention. $linearize_\theta$ is a transformation from a higher-dimensional space (2 in our case) to a single dimension space. The transformation does learn weights on different tokens in the input which can be thought of as attention. However, attention mechanisms do not necessarily perform dimensionality reduction which is the key component of $linearize_\theta$. In Section 5 we empirically demonstrate better model accuracy when we summarize with $linearize_\theta$ rather than $concat_s$.

3.2.3 Edit-Aware Alignment

In addition to input length, **CH1** also alludes that an effective input representation needs to be "edit aware". The aforementioned representations do not provide any indication that A and B are edits from O.

Prior work, *Learning to Represent Edits* (LTRE) [48] introduces a representation to succinctly encode 2 two-way diffs. The method uses a standard deterministic diffing algorithm and represents the resulting pair-wise alignment as an auto-encoded fixed dimension vector.

A two-way alignment produces an "edit sequence". This series of edits, if applied to the second sequence, would produce the first. An edit sequence, Δ_{AO}, is comprised of the following editing actions: $=$ representing equivalent tokens, $+$ representing insertions, $-$ representing deletions, $\leftrightarrow$ representing a replacement. Two special tokens $\emptyset$ and $|$ are used as a padding token and a newline marker, respectively. Note that these Δs only capture information about the *kinds* of edits and *ignore* the the tokens that make up the edit itself (with the exception of the newline token). Prior to the creation of Δ, a preprocessing step adds padding tokens such that equivalent tokens in A (resp. B) and O are in the same position. These sequences, shown in Figure 5 are denoted as A' and AO' (resp. B' and BO').

Example 3. Consider B's edit to O in Figure 5 via its preprocessed sequences B', BO', and its edit sequence Δ_{BO}. One intuitive view of Δ_{BO} is that it is a set of

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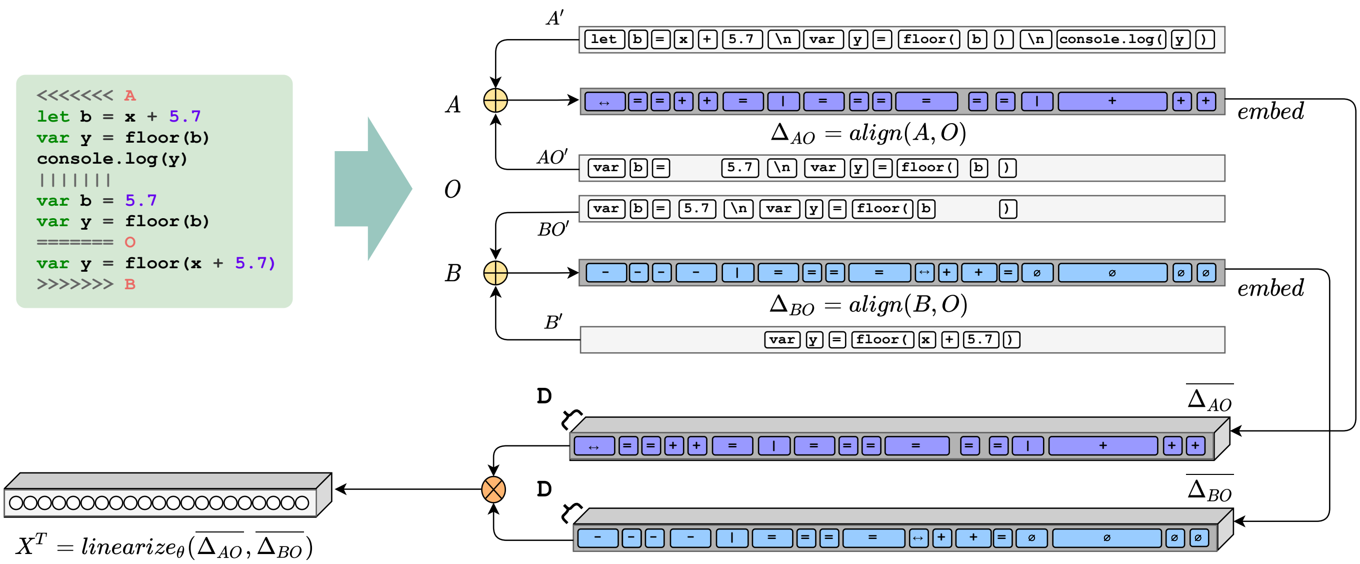

Figure 5: *Merge2Matrix*: implemented with the Aligned Linearized input representation used in DEEPMERGE.

instructions that describe how to turn B' into BO' with the aforementioned semantics. Note the padding token $\emptyset$ introduced into Δ_{BO} represents padding out to the length of the longer edit sequence Δ_{AO}. □

We now describe two edit-aware summarization methods based on this edit-aware representation. However, our setting differs from the original *LTRE* setting as we assume three input sequences and a three-way diff. In the following summarization methods, we assume that A, B, O are tokenized, but *not* embedded before invoking *Merge2Matrix*.

Aligned *naïve*. Given Δ_{AO} and Δ_{BO}, we embed each to produce $\overline{\Delta_{AO}}$ and $\overline{\Delta_{BO}}$, respectively. Then we combine these embeddings through concatenation and thus $concat_2(\overline{\Delta_{AO}}, \overline{\Delta_{BO}})$ is fed to the encoder.

Aligned linearized. This summarization method is depicted in Figure 5, invoking $linearize$ to construct an input representation over edit sequences. First, we apply alignment to create Δ_{AO} and Δ_{BO}. This is portrayed through the $\bigoplus$ operator. Following construction of the Δs, we apply embedding and subsequently apply our edit-aware linearize operation via the $\bigotimes$ operator. Thus, we summarize embeddings with $linearize_\theta(\overline{\Delta_{AO}}, \overline{\Delta_{BO}})$ and feed its output to the encoder. As we demonstrate in Section 5, this edit-aware input representation significantly increases the model's accuracy.

LTRE. Finally, for completeness, we also include the original *LTRE* representation. We modify this to our setting by creating *two* 2-way diffs. The original *LTRE* has a second key difference from our summarization methods. *LTRE* includes all tokens from from the input sequences in addition to the edit sequences That is, *LTRE* summarizes A' AO', Δ_{AO}, B', BO', and Δ_{BO}. Let $\overline{A'}$, $\overline{AO'}$ and $\overline{\Delta_{AO}}$, (resp $\overline{B'}$, $\overline{BO'}$, and $\overline{\Delta_{BO}}$) be the embedding of a two-way diff. Then, the following summarization combines all embeddings:

$$concat_6(\overline{\Delta_{AO}}, \overline{A'}, \overline{AO'}, \overline{\Delta_{BO}}, \overline{B'}, \overline{BO'})$$

3.3 The Encoder

The prior sections described *Merge2Matrix* which embeds a merge into a continuous space which is then summarized by an encoder. DEEPMERGE uses a bi-directional gated recurrent unit[9] (GRU) to summarize the embedded input sequence. Similar to other approaches applying neural techniques to source code [49], we empirically found that a bi-directional GRU provided better results than a uni-directional GRU.

3.4 Synthesizing Merge Resolutions

This section summarizes DEEPMERGE's approach to solving **CH2**. Given a sequence of hidden vectors Z_N produced by an encoder, a decoder generates output sequence Y_M. We introduce an extension of a traditional decoder to copy lines of code from those input programs.

Denote the number of lines in A and B as Li_A and Li_B, respectively. Suppose that $L = 1..(Li_A + Li_B)$; then, a value $i \in L$ corresponds to the i-th line from A if $i <= Li_A$, and the $i - Li_A$-th line from B, otherwise.

Given merge inputs (A, B, O), DEEPMERGE's decoder computes a sequence of hidden states H_M, and models the conditional probability of *lines* copied from the input programs A, B, and O by predicting a value in $y_m \in Y_M$:

$$p(y_m | y_1, ..., y_{m-1}, A, B, O) = softmax(h_m)$$

where $h_m \in H_M$ is the decoder hidden state at the m-th element of the output sequence and the $argmax(y_m)$ yields an index into L.

In practice, we add an additional $\langle$STOP$\rangle$ token to L. The $\langle$STOP$\rangle$ token signifies that the decoder has completed the sequence. The $\langle$STOP$\rangle$ token is necessary as the decoder may output a variable number of lines conditioned on the inputs.

This formulation is inspired by pointer networks [44], an encoder-decoder architecture that outputs an index that explicitly points to an input token. Such networks are designed to solve combinatorial problems like sorting. Because the size of the output varies as a function of the input, a pointer

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network requires a novel attention mechanism that applies attention weights directly to the input sequence. This differs from traditional attention networks which are applied to the outputs of the encoder Z_N. In contrast, DEEPMERGE requires no change to attention. Our architecture outputs an index that points to the abstract concept of a line, rather than an explicit token in the input. Thus, attention applied to Z_N, a summarization of the input, is sufficient.

3.5 Training and Inference with DEEPMERGE

The prior sections discussed the overall model architecture of DEEPMERGE. This section describes hyperparameters that control model size and how we trained the model. We use a embedding dimension $D = 1024$ and 1024 hidden units in the single layer GRU encoder. Assume the model parameters are contained in θ; training seeks to find the values of θ that maximize the log-likelihood

$$\arg\max_{\theta} \log p_\theta(R|A, B, O)$$

over all merge tuples ((A, B, O), R) in its training dataset. We use standard cross-entropy loss with the Adam optimizer. Training takes roughly 18 hours on a NVIDIA P100 GPU and we pick the model with the highest validation accuracy, which occurred after 29 epochs.

Finally, during inference time, we augment DEEPMERGE to use standard beam search methods during decoding to produce the most likely k top merge resolutions. DEEPMERGE predicts merge resolutions up to C lines. We set $C = 30$ to tackle implementation constraints and because most resolutions are less than 30 lines long. However, we evaluate DEEPMERGE on a full test dataset including samples where the number of lines in M is $\geq C$.

4 REAL-WORLD LABELED DATASET

To build our dataset, we identify merge conflicts and their resolutions in a git repository history. For each file in a merge commit, we extract the version of the file in the last commit in both branches involved in the merge (the commit just preceding the merge), yielding $\mathcal{A}$ and $\mathcal{B}$. We also identify the commit representing the common base of both branches and extract the version of the file from that commit, which provides $\mathcal{O}$. Finally, we extract the version of the file in the merge commit (which has presumably been resolved by the author) which we treat as the correctly merged file, $\mathcal{M}$. Running `diff3` with $\mathcal{O}$, $\mathcal{A}$, and $\mathcal{B}$ indicates if there is a merge conflict in the file and produces a conflict file with conflict region markers (For an example, see Figure 6-a). However, matching conflict regions (denoted by the conflict markers) in the conflict file with corresponding resolutions in $\mathcal{M}$ is non-trivial.

This section describes our solution to **CH3**: localizing merge instances $(A, B, O, R)_i$ from $(\mathcal{A}, \mathcal{B}, \mathcal{O}, \mathcal{M})$. Since a program may have several merge conflicts, we decompose the overall merge problem into merging individual instances. As shown in Figure 3, A, B, and O regions can be easily extracted given the `diff3` conflict markers. However, reliably localizing a resolution R involves two sub-challenges:

1) How do we localize individual regions R unambiguously?
2) How do we deal with trivial resolutions?

In this section, we elaborate on each of these sub-challenges and discuss our solutions. We conclude with a discussion of our final dataset and its characteristics.

Algorithm 1 Localizing Merge Tuples from Files for Dataset

1: **procedure** LOCALIZEMERGETUPLES($\mathcal{C}$, $\mathcal{M}$)
2: $\quad MT \leftarrow \emptyset$ ▷ Merge Tuples
3: $\quad$ **for** $i \in$ [1, NUMCONFLICTS($\mathcal{C}$)] **do**
4: $\quad\quad R \leftarrow$ LOCALIZERESREGION($\mathcal{C}, \mathcal{M}, i$)
5: $\quad\quad$ **if** $R ==$ `nil` **then**
6: $\quad\quad\quad$ **continue** ▷ Could not find resolution
7: $\quad\quad$ **end if**
8: $\quad\quad (A, B, O) \leftarrow$GETCONFLICTCOMPONENTS($\mathcal{C}, i$)
9: $\quad\quad$ **if** $R \in \{A, B, O\}$ **then**
10: $\quad\quad\quad$ **continue** ▷ Filter trivial resolutions
11: $\quad\quad$ **end if**
12: $\quad\quad$ **if** LINES(R) $\subseteq$ LINES(A) $\cup$ LINES(B) **then**
13: $\quad\quad\quad MT \leftarrow MT \cup \{(A, B, O, R)\}$
14: $\quad\quad$ **end if**
15: $\quad$ **end for**
16: $\quad$ **return** MT
17: **end procedure**

18: **procedure** LOCALIZERESREGION($\mathcal{C}$, $\mathcal{M}$, i)
19: $\quad n \leftarrow Length(\mathcal{M})$ ▷ Length of $\mathcal{M}$ in chars
20: $\quad m \leftarrow Length(\mathcal{C})$ ▷ Length of $\mathcal{C}$ in chars
21: $\quad (spos, epos) \leftarrow$ GETCONFLICTSTARTEND($\mathcal{C}, i$)
22: $\quad prfx \leftarrow \langle BOF \rangle + \mathcal{C}[0 : spos]$
23: $\quad sffx \leftarrow \mathcal{C}[epos : m] + \langle EOF \rangle$
24: $\quad$ s $\leftarrow$ MINIMALUNIQUEPREFIX($reverse(prfx), reverse(\mathcal{M})$)
25: $\quad$ e $\leftarrow$ MINIMALUNIQUEPREFIX($sffx, \mathcal{M}$)
26: $\quad$ **if** $s \geq 0$ and $e \geq 0$ **then**
27: $\quad\quad$ **return** $\mathcal{M}[n - s : e]$
28: $\quad$ **else**
29: $\quad\quad$ **return** `nil`
30: $\quad$ **end if**
31: **end procedure**

32: **procedure** MINIMALUNIQUEPREFIX(x, y)
33: $\quad$ **Output:**Returns the start position of the minimal non-empty prefix of x that appears uniquely in y, else -1
34: **end procedure**

35: **procedure** LINES(p)
36: $\quad$ **Output:**Returns the set of lines comprising the program p
37: **end procedure**

Algorithm 1 denotes a method to localize merge tuples from a corpus of merge conflict and resolution files. The top-level procedure EXTRACTMERGETUPLES takes $\mathcal{C}$, the `diff3` conflict file with markers, along with $\mathcal{M}$, the resolved file. From those inputs, it extracts merge tuples into MT. The algorithm loops over each of the conflicted regions in $\mathcal{C}$, and identifies the input (A, B, O) and output (R) of the tuple using GETCONFLICTCOMPONENTS and LOCALIZERESREGION respectively. Finally, it applies a filter on the extracted tuple (lines 5 – 14). We explain each of these components in the next few subsections.

4.1 Localization of Resolution Regions

Creating a real-world merge conflict labeled dataset requires identifying the "exact" code region that constitutes a resolution. However, doing so can be challenging; Figure 6 demonstrates an example. The developer chooses to perform a resolution `baz();` that does not correspond to anything from the A or B edits, and the surrounding context also undergoes changes (e.g. changing var with let which restricts

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```
<BOF>
...
var time = new Date();
print_time(time);
<<<<<<< a.js
x = foo();
||||||| base.js
=======
x = bar();
>>>>>>> b.js
print_time(time);
<EOF>
```

(a) A merge instance.

```
<BOF>
...
let time = new Date();
print_time(time);
baz();
print_time(time);
<EOF>
```

(b) Resolution.

Figure 6: Challenging example for localizing resolution. Red code indicates the minimally unique suffix of the code preceding the conflict region and blue indicates the minimally unique prefix of the code succeeding the conflict region.

the scope in the prefix). To the best of our knowledge, there is no known algorithm to localize R for such cases.

LOCALIZERESREGION is our method that tries to localize the i^{th} resolution region R, or returns `nil` when unsuccessful. Intuitively, we find a prefix and suffix in a merge instance and use this prefix and suffix to bookend a resolution. If we cannot uniquely find those bookends, we say the resolution is *ambiguous*.

The method first obtains the prefix $prfx$ (resp. suffix $sffx$) of the i^{th} conflict region in $\mathcal{C}$ in line 22 (resp. line 23). We add the start of file $\langle BOF \rangle$ and end of file $\langle EOF \rangle$ tokens to the prefix and suffix respectively.

The next few lines try to match the prefix $prfx$ (resp. suffix $sffx$) in the resolved file $\mathcal{M}$ unambiguously.

For simplicity, let us first focus on finding the suffix of the resolution region in $\mathcal{M}$ in line 25. The procedure MINIMALUNIQUEPREFIX takes two strings x and y and finds the start position of the minimal non-empty prefix of x that appears uniquely in y, or returns -1. For example, MINIMALUNIQUEPREFIX("abc", "acdabacc") is 3 since "ab" is the minimal prefix of x that appears uniquely in y starting in position 3 (0-based indexing).

In our running example from Figure 6, x is $sffx$, the code following the conflict region:

```
print_time(time);
<EOF>
```

and y is the entire resolution (figure 6-b). Note that "`print_time(time);`" occurs twice in the resolution, so the minimal non-empty prefix of x that occurs *uniquely* must include the `<EOF>` token. This is indicated by the blue text in Figure 6.

To find the prefix of the resolution, we reverse the $prfx$ string and search for matches in reversed $\mathcal{M}$, and then finally find the offset from the start of $\mathcal{M}$ by subtracting s from the length n of $\mathcal{M}$.

Returning to our running example, this means we need to find the minimal non-empty prefix of the code that precedes the conflict region. Code that is reversed character by character is difficult to read and make sense of, so we avoid that shoing both strings in reverse below. In place of that it's helpful to recognize that looking for the minimally unique *prefix* of one reversed string in another reversed string is equivalent to finding the minimally unique *suffix* of the first string in the second string (code that is reversed character by character can be difficult to follow). We therefore color the suffix of strings below rather than the prefix of the reversed strings for ease of the reader.

Below is $prfx$, the code preceding the conflict region. Our aim is to find the smallest suffix of this code that occurs exactly once in the resolution.

```
<BOF>
...
var time = new Date();
print_time(time);
```

For reference, the resolution is:

```
<BOF>
...
var time = new Date();
print_time(time);
baz();
print_time(time);
<EOF>
```

Again, note that matching the line "`print_time(time);`" is not minimally unique because it occurs twice in the resolution. Working backwards from that line, it is not until the "`e();`" from the "`Date();`" in the previous line is included that $prfx$ provides a unique match in $\mathcal{M}$. We indicate this in the minimal unique match in $prfx$ and $\mathcal{M}$ above and in Figure 6 by using red text (note the end of the third line of code in both listings is also red).

Having identified the end of prefix of the conflict region (red) and the beginning of the suffix of the conflict region (blue), both which match in exactly one location in $\mathcal{M}$, these serve to bookend the resolution, enabling us to identify and extract "`baz();`" as R, the resolution region (line 27).

After localizing the resolution regions, we have a set of merge instances of the form (A, B, O, R). We can use our definition from Section 2 to label a merge tuple (A, B, O, R).

4.1.1 *Validation of* LOCALIZERESREGION

To evaluate LOCALIZERESREGION we performed a manual analysis. We selected 50 merge conflicts at random for inspection. For each conflict, we then generated the merge conflict file (with the merge conflict markers identifying A, B, and O) and also extracted the actual developer resolved version of the file (the version of the file containing R). We then ran LOCALIZERESREGION on every conflict region in each conflict to extract the resolution region and also examined both files (with the aid of a side-by-side diff viewer) to manually identify the resolution region.

In all, there were 174 conflict regions in the 50 merge conflicts. LOCALIZERESREGION identified the correct merge resolution region in all 174 cases. An exact binomial test [18] at the 95% level gives a confidence interval of [0.979, 1.0], indicating that given these results, there is a 95% likelihood that the true accuracy of LOCALIZERESREGION is between 97.9% and 100%. Given this level of performance, we use it confidently to extract resolution regions in our data sets.

4.2 Filtering Trivial Resolutions

Upon examining our dataset, we found a large set of merges in which A was taken as the resolution and B was entirely ignored (or vice versa). These trivial samples, in large, were (likely) the product of running *git merge* with "ours" or "theirs" command-line options. Using these merge options indicates that the developer did not resolve the conflict after careful consideration of both branches, but instead relied on the git interface to completely drop one set of changes. The aforementioned command-line merge options are typically used the commit is the first of many fix-up commits to perform the full resolution.

We appeal to the notion of a "valid merge" that tries to incorporate both the syntactic and semantic changes from both A and B. Thus, these samples are not valid as they disregard the changes from B (resp. A) entirely. Furthermore, these trivial samples comprised 70% of our "pre-filtering" dataset. Previous work confirmed our observation that a majority of merge resolutions in GitHub Java projects (75% in Table 13 [13]) correspond to taking just A or B. To avoid polluting our dataset, we filter such merges (A, B, O, R) where $R \in \{A, B, O\}$ (line 9 in Algorithm 1). Our motivation to filter the dataset of trivial labels is based on both dataset bias and the notion of a valid merge.

4.3 Final Dataset

We crawled repositories in GitHub containing primarily JavaScript files, looking at merge commits. We chose JavaScript as the language of focus for evaluation due to its importance and growing popularity and the fact that static analysis of JavaScript is challenging due to its weak, dynamic type system and permissive nature [19], [23]. Gathering data from GitHub indiscriminately can lead to both noise and bias. We address this by following the advice of Kalliamvakou *et al.* [21], We select projects that were active in the past one year (at the time of writing), and received at least 100 stars (positive sentiment). In all, our training data-set comprised 1126 JavaScript repositories. We also verified that the dataset did not contain duplicate merges. We ignore *minified* JavaScript files that compress an entire JavaScript file to a few long lines. Finally, note that Algorithm 1 filters away any resolution that consists of new segments (lines) outside of A and B as our technique targets resolutions that do not involve writing any new code. After applying filters, we obtained 8,719 merge tuples. We divided these into a 80/10/10 percent training/validation/test split. This complete dataset contains the following distribution in terms of total number of lines in A and B: 45.08% ([0,5]), 20.57% ([6,10]), 26.42% ([11,50]), 4.22% ([51,100]) and 3.70% (100+).

5 Evaluation

In this section, we empirically evaluate DeepMerge to answer the following questions:

RQ1 How effective is DeepMerge at synthesizing resolutions?

RQ2 How effective is DeepMerge at suppressing incorrect resolutions?

RQ3 On which samples is DeepMerge most effective?

RQ4 How do different choices of input representation impact the performance of DeepMerge?

5.1 RQ1: Effectiveness of Resolution Synthesis

In this section, we perform an evaluation to assess DeepMerge's effectiveness of synthesizing resolutions. Our prediction, $\hat{R}$, is considered correct if it is an exact (line for line, token for token) match with R.

	Top-1	Top-3
DeepMerge	**36.50%**	**43.23%**
ScanMerge	4.20%	7.43%
Seq2Seq	2.3%	3.3%
jsFSTMerge	3.7%	N/A

Table 1: Evaluation of DeepMerge and baselines: resolution synthesis accuracy (%).

Evaluation metrics. DeepMerge produces a ranked list of predictions; we define top-1 (resp. top-3) accuracy if the R is present in first (resp. top 3) predictions. This is a lower bound, as multiple resolutions may be "correct" with respect to the semantics of the changes being merged (e.g., in some cases, switching two declarations or unrelated statements has no impact on semantics).

Quantitative Results. Table 1 shows the performance of DeepMerge on a held out test set. DeepMerge has an overall top-1 accuracy of 36.5%, correctly generating more than one in three resolutions as its first ranked choice. When we consider the top-3 ranked resolutions, DeepMerge achieves a slightly improved accuracy of 43.23%.

Baselines. Table 1 also includes a comparison of DeepMerge to three baselines. We compare to a heuristic based approach (ScanMerge), an off-the-shelf sequence-to-sequence model (Seq2Seq), and a structured AST based approach (jsFSTMerge).

Our first baseline ScanMerge, is a heuristic based approach designed by manually observing patterns in our dataset. ScanMerge randomly samples from the space of sub-sequences over lines from A and B that fulfill the following constraints:

(i) The code produced is syntactically valid and parses.

(ii) The resolution includes every line from A and every line from B. Intuitively, no part of the change in A or the change in B is discarded.

(iii) The relative order of lines within A and within B is maintained within the resolution. If line x precedes line y in A, then x must precede y in the resolution, even if lines from B are interspersed between them.

These heuristic restrictions are based on manual observations that a large majority of resolutions satisfy these conditions.

Table 1 shows ScanMerge's performance averaged over 10 trials. DeepMerge performs significantly better in terms of top-1 resolution accuracy (36.50% vs 4.20%). ScanMerge only synthesizes one in 20 resolutions correctly. In contrast, DeepMerge correctly predicts one in 3 resolutions. On inputs of 3 lines or less, ScanMerge only achieves 12% accuracy suggesting that the problem space is large even for small merges.

We also compared DeepMerge to an out of the box sequence-to-sequence encoder-decoder model [40] (Seq2Seq) implemented with Fairseq [4] natural language processing library. Using a *naïve* input (i.e., $concat_3(A, B, O)$), tokenized with a standard byte-pair encoding, and Fairseq's default parameters, we trained on the

4. https://github.com/pytorch/fairseq

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Threshold	[1,3] lines	[4,5] lines	[6,7] lines	[8,10] lines	[>10] lines
0	78.40%	56.50%	37.04%	10.87%	2.93%

Table 2: Evaluation of DEEPMERGE: accuracy vs input size (%).

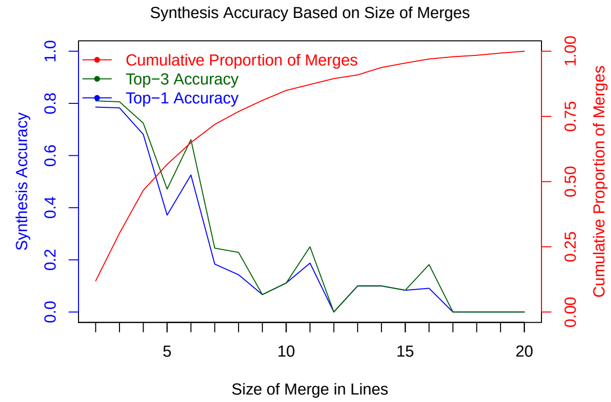

Figure 7: DEEPMERGE's performance vs merge input size. Cumulative distribution of merge sizes in red.

same dataset as DEEPMERGE. DEEPMERGE outperforms the sequence-to-sequence model in terms of both top-1 (36.5% vs. 2.3%) and top-3 accuracy (43.2% vs. 3.3%). This is perhaps not surprising given the precise notion of accuracy that does not tolerate even a single token mismatch. We therefore also considered a more relaxed measure, the BLEU-4 score [34], a metric that compares two sentences for "closeness" using an n-gram model. The sequence-to-sequence model achieves a respectable score of 27%, however DEEPMERGE still outperforms with a BLEU-4 score of 50%. This demonstrates that our novel embedding of the merge inputs and pointer network style output technique aid DEEPMERGE significantly and outperform a state of the art sequence-to-sequence baseline model.

Lastly, we compared DEEPMERGE to JSFSTMERGE[42], a recent semistructured AST based approach. JSFSTMERGE leverages syntactic information by representing input programs as ASTs. With this format, algorithms are invoked to safely merge nodes and subtrees. Structured approaches do not model semantics and can only safely merge program elements that do not have side effects. Structured approaches have been proven to work well for statically typed languages such as Java [3], [25]. However, the benefits of semistructured merge hardly translate to dynamic languages such as JavaScript. JavaScript provides less static information than Java and allows statements (with potential side effects) at the same syntactic level as commutative elements such as function declarations.

As a baseline to compare to DEEPMERGE, we ran JSFSTMERGE with a timeout of 5 minutes. Since JSFSTMERGE is a semistructured approach we apply a looser evaluation metric. A resolution is considered correct if it is an exact syntactic match with R *or* if it is semantically equivalent. We determine semantic equivalence manually. JSFSTMERGE produces a correct resolution on 3.7% of samples which is significantly lower than DEEPMERGE. Furthermore, JSFSTMERGE does not have support for predicting Top-k resolutions and only outputs a single resolution. The remaining 96.3% of cases failed as follows. In 92.1% of samples, JSFSTMERGE was not able to produce a resolution and reported a conflict. In 3.3% of samples, JSFSTMERGE took greater than 5 minutes to execute and was terminated. In the remaining 0.8% JSFSTMERGE produced a resolution that was both syntactically and semantically different than the user's resolution. In addition to effectiveness, DEEPMERGE is superior to JSFSTMERGE in terms of execution time. Performing inference with deep neural approaches is much quicker than (semi) structured approaches. In our experiments, JSFSTMERGE had an average execution time of 18 seconds per sample. In contrast, sequence-to-sequence models such as DEEPMERGE perform inference in under a second.

Sensitivity to Input Merge Conflict Size. We observe that there is a diverse range in the size of merge conflicts (lines in A plus lines in B). However, as shown in Figure 7, most (58% of our test set) merges are small, consisting of 7 or less lines. As a product of the dataset distribution and problem space size, DEEPMERGE performs better for smaller merges. We present aggregate Top-1 accuracy for the input ranges in Table 2. DEEPMERGE achieves over 78% synthesis accuracy on merge inputs consisting of 3 lines or less. On merge inputs consisting of 7 lines or less (58% of our test set) DEEPMERGE achieves over 61% synthesis accuracy.

> DEEPMERGE achieves a top-1 accuracy of 36.50% and top-3 accuracy of 43.23%. It shows 61% accuracy on merges 7 lines or less in size. DEEPMERGE outperforms a state of the art structured merge approach (JSFSTMERGE with 3.7% top-1 accuracy) as well as baseline and Naïve neural approaches.

5.2 RQ2: Effectiveness of Suppressing Incorrect Resolutions

The probabilistic nature of DEEPMERGE allows for accommodating a spectrum of users with different tolerance for incorrect suggestions. "Confidence" metrics can be associated with each output sequence to suppress unlikely suggestions. In this section, we study the effectiveness of DEEPMERGE's confidence intervals.

In the scenario where DEEPMERGE cannot confidently synthesize a resolution, it declares a conflict and remains silent without reporting a resolution. This enables DEEPMERGE to provide a higher percentage of correct resolutions (higher precision) at the cost of not providing a resolution for every merge (lower recall). This is critical for practical use, as prior work has shown that tools with a high false positive rate are unlikely to be used by developers [20]. Figure 8 depicts the precision, recall, and F1 score values, for various confidence thresholds (with 95% confidence intervals). We aim to find a threshold that achieves high precision without sacrificing too much recall. In Figure 8, the highest F1-Score of 0.46 is achieved at 0.4 and 0.5. At threshold of 0.5, DEEPMERGE's top-1 precision is 0.72 with a recall of 0.34. Thus, while DEEPMERGE only produces a

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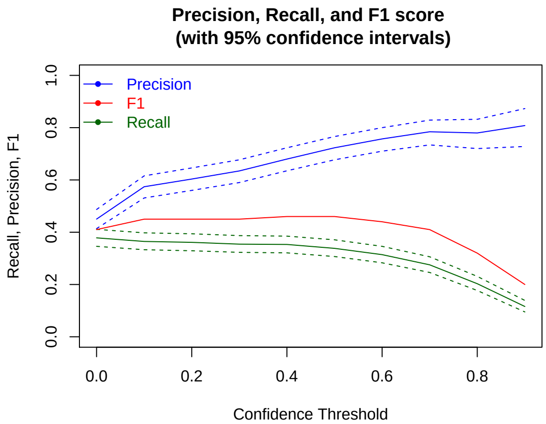

Figure 8: Top-1 precision and recall by confidence threshold.

Class	Top-1 Accuracy	Percent of Dataset
CONCAT	44.40%	26.88%
OTHER	29.03%	73.12%

Table 3: Accuracy and Distribution of classes.

resolution one third of the time, that resolution is correct three out of four times. Compared to DEEPMERGE with no thresholding, at a threshold of 0.5 DEEPMERGE achieves a 2x improvement in precision while only sacrificing a 10% drop in recall. Thresholds of 0.4 and 0.5 were identified as best performing on a held out validation set. We then confirmed that these thresholds were optimal on the held out test set reported in Figure 8.

> When using a threshold to suppress low confidence resolutions, DEEPMERGE is able to achieve top-1 accuracy of 72% (precision), providing resolution suggestions for 34% (recall) of conflicts.

5.3 RQ3: Categorical Analysis of Effectiveness

We now provide an analysis of DEEPMERGE's performance. To understand which samples DEEPMERGE is most effective at resolving, we classify the dataset into two classes: `CONCAT` and `OTHER`. The classes are defined as follows:

1) **`CONCAT`** - resolutions of the form AB or BA. Specifically:
   - R contains all lines in A and all lines in B.
   - There is no interleaving between A's lines and B's lines.
   - The order of lines within A and B is preserved.
2) **`OTHER`** - resolutions not classified as `CONCAT`. `OTHER` samples can be any interleaving of any subset of lines.

Table 3 shows the performance of DEEPMERGE on each class. DEEPMERGE performs comparably well on each category suggesting that DEEPMERGE is effective at resolving conflicts beyond concatenation.

	Top-1	Top-3
Naïve	9.62%	14.09%
Linearized	15.25%	19.95%
LTRE	23.37%	29.21%
Aligned Naïve	27.41%	32.22%
Aligned Linearized	**36.50%**	**43.23%**

Table 4: Accuracy of different input representation choices.

> DEEPMERGE performs best on conflicts whose resolution is all of A followed by all of B (or vice versa), achieving a top-1 accuracy of 44%

5.4 RQ4: Impact of Input Representation

We now evaluate the use of *Merge2Matrix* and show the benefit of the **Aligned Linearized** implementation used in DEEPMERGE.

We evaluate DEEPMERGE on each combination of summarization and edit aware alignment described in Section 3.2: *Naïve*, *Linearized*, *LTRE*, *Aligned naïve*, and *Aligned Linearized*. Table 4 shows the performance of each input representation on detection and synthesis. The edit-aware input formats: *LTRE*, *Aligned Naïve*, and *Aligned Linearized* attain an improvement over the edit-unaware formats. Our *Aligned* representations are more succinct and contribute to a large increase in accuracy over the edit-unaware formats. *Aligned Naïve* increases accuracy over our best edit-unaware format by 12.16% for top-1 and 12.27% for top-3. We believe this is due to the verbosity of including the underlying tokens as well as the Δ edit sequence. The combination of our edit-aware and summarization insights (*Aligned Linearized*) yields the highest accuracy.

> The *Aligned Linearized* representation yields the best results, with improvements of to 9% to 27% in top-1 accuracy over other representations (11% to 29% for top-3 accuracy).

5.5 Incorrect Predictions

In an effort to understand how and why DEEPMERGE get some merge conflict resolutions wrong, we manually examined 50 incorrect merge suggestions. In each case, we examined the original code, O, the two changes to the code, A and B, the actual resolution R and the suggested resolution from DEEPMERGE.

There were many cases where the suggestion from DEEPMERGE was simply wrong for no apparent reason. However, during our manual analysis, there were some patterns and common cases that emerged that can inform future refinements of our approach.

Mixed additions and deletions: In at least five of the incorrect cases, one branch only removed code (sometimes *all* of the code in O) and the other branch only added code. In these cases, DEEPMERGE tends to simply take the additional code from one branch, but doesn't remove the code deleted in the other.

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Missing closing symbols: In twelve cases out of 50, DEEPMERGE fails to include at least one line that consists only of a closing symbol (parenthesis, brace, or bracket). Since these lines typically have only one character and often there are other lines already included in the resolution that consist solely of the same character, we hypothesize that the model "gets confused" and neglects to include all closing punctuation. One might wonder why the same issue doesn't occur with opening symbols, but we observed that opening symbols, such as the beginning of a list or of a function, often come at the end of a line with preceding code such as a variable name, function signature, or if condition. Note that accepting these suggested resolutions would yield code that is syntactically incorrect because of unbalanced delimiters.

Same line included twice in different forms: In five cases, a line of code in O was modified slightly differently in A and in B and the suggestion from DEEPMERGE included both versions of the line. This often led to code that contained semantic issues such as two declarations of the same variable with different values or types.

Large conflicts: Many of the incorrect suggestions were for conflicts that were bigger than normal. Often the suggestions were very similar to the actual resolution, but differed in one or two places; We computed the ROUGE-2 score [27] between the DEEPMERGE suggested resolution and the actual resolution for each conflict and even for large conflicts it was often over 0.8. Intiuitively, we believe that it makes sense that larger conflicts are more likely to be incorrect because they contain more "decision points" where the model must select which line from the input sequences should be included in the suggested resolution. Even if each individual choice made by the model about which line to include at a given point has a high probability of being correct, the likelihood of *all* such choices being correct for a resolution drops as the number of choices (i.e., lines) goes down as the numnber of choices goes up. *Any* wrong choice will lead to the suggested resolution not matching the actual resolution and will be considered incorrect.

Semantically equivalent code: Finally, in eleven cases, the resolution suggested by DEEPMERGE was textually different from, but semantically equivalent to, the actual resolution. Most often this took the form of a slightly different order of import statements or a slightly different order of items added to a list. In these cases, we checked to see if there was a pattern to the ordering (e.g., alphabetical order) which might indicate that a particular order was preferred, but we didn't identify any. The other cases were merges where statements or declarations that were independent from each other were ordered differently in the DEEPMERGE suggestion than in the actual resolution.

This last category indicates that DEEPMERGE is actually doing better than our automated evaluation indicates, as we are not able to automatically detect semantically equivalent resolutions. Fixing the other cases is likely fairly challenging, but identifying them may be an easier task. For instance, one could use a parser to identify syntactically incorrect code and add a checker on the resultant abstract syntax tree to find duplicate declarations. Exploring methods for addressing these types of incorrect merge conflict resolution suggestions is an avenue for future research.

5.6 Summary of Results

Our evaluation and baselines indicate that the problem of synthesizing resolutions is a non-trivial task, even when restricted to resolutions that rearrange lines from the conflict. DEEPMERGE not only can synthesize resolutions for more than a third of times, but can also use its internal confidence to achieve high precision (72%). DEEPMERGE can synthesize resolutions significantly more accurately than heuristic based, neural, and structured approaches. We also illustrate the need for edit-aware aligned encoding of merge inputs to help deep learning be more effective synthesizing non-trivial resolutions.

6 Threats to Validity

As with any empirical investigation, our choice of dataset may be impacted by threats to validity [31]. We outline the key threats to validity and our mitigation strategies in this section.

External Validity is concerned with the generalizability of our results. To achieve generalizability, the sample data sets we train on and evaluate on must be representative of the population of merge conflict resolutions. To ensure that our dataset consists of representative merges, we sampled merge conflict resolutions from over 1126 software repositories on GitHub. Gathering data from GitHub indiscriminately can lead to both noise and bias. We address this by following the advice of Kalliamvakou *et al.* [21] and select projects that have recent activity, received a large number of stars (positive sentiment), and include a non-trivial number of contributors. Finally, there may be more than one correct merge resolution, such that using the recorded resolution as the oracle is incomplete. In this context, the results of DEEPMERGE may actually be better than reported, as it may be producing resolutions that do not match the oracle, but are nonetheless correct.

Internal Validity refers to the factors that may affect the reliability of the results of the experiments. For both training and evaluation of DEEPMERGE, we require an oracle for each merge conflict resolution. Fortunately, we have a wealth of historical merge conflicts and resolutions that occurred in practice and thus we are able to treat the actual recorded resolutions as the oracle. We note that two potential issues with this approach. First, developers may not always resolve a merge correctly. We manually investigated a sample of commits and did not see evidence of modifying the merges in subsequent commits. Second, there may be more than one correct merge resolution, such that using the recorded resolution as the oracle is incomplete. In this context, the results of DEEPMERGE may actually be better than reported, as it may be producing resolutions that do not match the oracle, but are nonetheless correct.

In terms of implementation, we rely on existing, well vetted tooling in both our data collection and model implementation. For example, we identify differences and conflicts using the well known `diff3` tool and our models are all built using the PyTorch framework. While we cannot unequivocally state that our implementation is free of errors, we are confident in it because we employ Q/A practices such as code review in our development and we have manually investigated the results heavily.

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7 DISCUSSION

Having demonstrated that DEEPMERGE achieves high precision and works well on real-world merge conflicts, we now discuss how we envision it's usage in the software development process and share lessons learned during the development and evaluation of DEEPMERGE.

7.1 Integration into the Development Pipeline

We are currently exploring the best ways to integrate DEEPMERGE in the development process. Since the accuracy of DEEPMERGE is not 100%, we do not envision this to be a completely automatic tool that resolves merge conflicts without a developer's involvement. Rather, we believe that DEEPMERGE can save developers valuable time by providing high confidence suggestions to supplant manual code editing in two potential usage scenarios.

First, when a developer attempts to merge their branch into another, an IDE may recognize a conflict either through hooks in `git` that are executed upon a conflict or from the presence of conflict markers in source code files. The IDE would then invoke DEEPMERGE and offer the developer the choice to accept a synthesized resolution and have it applied.

Second, if a proactive tool (e.g., Crystal [6]) determines that a conflict is imminent when a merge occurs, DEEPMERGE could be automatically employed to generate a merge conflict resolution as a Pull Request and a developer could accept, reject, or modify the suggestion.

It is also important to note that deep learning component of DEEPMERGE was trained on a large corpus of git repositories and can be used "off the shelf". It *does not* need to be trained on a specific repository in order to be used on that repository. The repositories used to evaluate DEEPMERGE in this paper were not part of the training corpus of data.

7.2 Lessons Learned and Future Directions

In our investigations of merge conflicts and our experience developing and evaluating DEEPMERGE, we believe that there are some key takeaways that are of benefit to the community as well as some clear directions for future research in the area of merge conflict resolution.

Merge conflicts resolutions rarely introduce any new tokens. In practice, the vast majority of merge conflict resolutions pull *all* of their code from the input conflicting code without a single new token. This finding severely constrains the merge resolution problem and makes solutions more tenable. DEEPMERGE achieves significant improvement using a pointer network to "recall" lines of code from A, B, and O over using a more general code generation approach (e.g., sequence to sequence models).

Neural models provide an intriguing alternative to structured merge. Structured merge approaches have existed for quite a few years and have decent performance. However, it is well known that these approaches suffer from the lack of types for dynamic languages such as Javascript [4]. We are encouraged that a neural model that works on lines of text with no structural information is able to significantly exceed the performance of a structured merge approach for such dynamic languages, in spite of the structured merge being tailored to semantics and structure of a particular language. This leads to further research directions, however. Combining both approaches by using structured representations such as that used for structured merge could potentially yield even better performance for merge conflict resolution, possibly even for languages with mature structured merge tools. How to go about this remains an open problem.

Line level granularity only goes so far. While we have demonstrated that DEEPMERGE works well, there are still a non-trivial amount of merges that comprise lines of text that don't exist in the A, B, or O even if the tokens do. Further work is required to explore how to resolve merge conflicts at the token, rather than the line, level.

Data curation is important. We encountered a number of challenges in extracting, filtering, and cleaning merge conflict data. Our experience has been that given enough data, it's usually possible to build an ML model that can work well on the data. However, the performance of such a model on real world tasks will be limited by the *quality* of the data. As an example, the need for the LOCALIZERESREGION algorithm came about because we identified issues in the resolutions in our data.

8 RELATED WORK

Our technique is related to several existing works in both program merging and deep learning for code.

8.1 Source Code Merging

The most widely used method for merging changes is `diff3`, the default for most version control systems. One reason for its popularity is that `diff3` is purely text based and therefore language agnostic. However, its behavior has been formalized and Khanna *et al.* showed that the trust developers have in it may be misplaced [24], including the examples in Figure 1.

There have been many attempts to improve merge algorithms by taking language specific analyses into account (see the work of Mens for a broad survey [29]). Westfechtel *et al.* use the structure of the source code to reduce merge conflicts [46]. Apel *et al.* noted that structured and unstructured merge each has strengths and weaknesses. They developed JSFSTMERGE, a *semi-structured merge*, that alternates between approaches [4]. They later introduced JDIME, an approach that automatically tunes a mixture of structured and unstructured merge based conflict locations [2]. Sousa *et al.* introduced a verification approach, SAFEMERGE that examines the base program, both changed programs, and the merge resolution to verify that the resolution preserves semantic conflict freedom [37].

The key difference between DEEPMERGE and these structured or semi-structured merge approaches is that they require a priori knowledge of the language of the merged code in the form of a parser or annotated grammar (or more advanced program verification tools). Further, structured merge tools cannot conservatively merge changes made within method bodies. Finally, Pan et al. [32] explore the use of program synthesis for learning repeated resolutions in a large project. The approach requires the design of a domain-specific languages inspired by a small class of resolutions (around imports and macros in C++). In contrast to both

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these approaches, DEEPMERGE only requires a corpus of merge resolutions in the target language, and can apply to all merge conflicts. However, we believe that both these approaches are complementary and can be incorporated into DEEPMERGE.

Our approach as well as the previous approaches discussed here deal with merge conflicts individually. In contrast, Shen *et al.* [35] leverage their insight that multiple conflicts in the same merge are often related in some way. They use graph algorithms on a graph representation of merge conflicts to cluster and order related conflicts and infer resolution strategies for unresolved conflicts based on already resolved ones.

8.2 Deep Learning on Source Code

We leverage deep neural network based natural language processing methods to address the challenge of three way merge resolution. We discuss related works in sequence-to-sequence learning that inspired our model and applications of deep learning for the software engineering domain.

Pointer networks [44] use attention to constrain general sequence-to-sequence models [40], [8]. Recent works incorporate a *copy* mechanism in sequence-to-sequence models by combining copying and token generation [16], adding a copying module in the decoder [50], and incorporating it into the beam search [33]. In contrast to DEEPMERGE, none of these approaches address the challenges described in Section 2 in a three-way merge.

Deep learning has been successfully used on source code to improve myriad software engineering tasks. These include code completion and code generation [41], [10], code search [17], software testing [14], defect prediction [45], and code summarization [1]. Deep learning has been used in program repair using neural machine translation [43], [7], sequence-editing approaches [33], and learning graph transformations [11]. For a deeper review of deep learning methods applied to software engineering tasks, see the literature reviews[26], [12].

While neural sequence-to-sequence models are utilized in most of those applications, they consume only one input sequence, mapping it to a single output sequence. Edit aware embeddings [48] introduced LTRE method to encode two program variants to model source code edits. As we demonstrate, our edit-aware encoding **Aligned Linearized** is inspired by this approach but significantly outperforms LTRE in the context of data-driven merge.

8.3 Studies of Code Repetition and Redundancy

Our key insight is related to, but different from, the "Plastic Survery Hypothesis"(PSH) introduced by Barr *et al.* [5]. In their paper, Barr *et al.* describe the PSH as having two parts. First, changes in a version of a program are repetitive relative to their parent, the program to which the changes are applied. Second, that this repetitiveness is usefully exploitable. The assertion of the PSH is that given a particular source code change, the majority of the lines in the change already exist *somewhere* in the codebase.

In the context of merge conflict resolutions, we make a stronger locality claim. Our key insight is that the lines in a merge conflict resolution most often come from from the set of lines that caused the conflict. This means that we limit where they come from (spatial locality) as well as when they were introduced (temporal locality). This observed property of merge conflict resolutions reduces the search space and makes finding a valid conflict resolution a tenable ML problem.

Martinez et al [28] introduced a similar idea of "Temporal Redundancy". By their definition "a [code] fragment is temporally redundant if that same fragment appeared in a previous commit." Further, they introduce a *local scope* notion of temporal redundancy in which the fragment has been used in a previous commit to the *same file*. The success of DeepMerge can be attributed to a more refined or constrained variant of this temporal redundancy, which beneficially limits the conflict resolution search space even further. We find that conflict resolutions rely primarily on fragments (lines in our case) that were introduced in the set of commits that exist on the branch between the common base (O) and the last commit on the branch prior to the merge. In addition, while Martinez *et al.* introduce *local* temporal redundancy which is constrained to code within the same file, we find that resolutions have even more constrained spatial locality; lines in the resolution primarily come from the lines that comprise the conflict in the merge.

9 CONCLUSION

We motivated the problem of *data-driven merge* and highlighted the main challenges in applying machine learning. We proposed DEEPMERGE, a data-driven merge framework, and demonstrated its effectiveness in resolving unstructured merge conflicts in JavaScript. We chose JavaScript as the language of focus in this paper due to its importance and growing popularity and the fact that analysis of JavaScript is challenging due at least in part to its weak, dynamic type system and permissive nature [19], [23]. We believe that DEEPMERGE can be easily extended to other languages and perhaps to any list-structured data format such as JSON and configuration files. We plan to combine program analysis techniques (e.g., parsing, typechecking, or static verifiers for merges) to prune the space of resolutions, and combine structured merge algorithms with machine learning to gain the best of both techniques. Furthermore, we plan to generalize our approach beyond line level output granularity.

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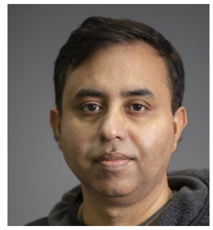

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