Can Pre-trained Language Models be Used to Resolve Textual and Semantic Merge Conflicts?

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ABSTRACT

Program merging is standard practice when developers integrate their individual changes to a common code base. When the merge algorithm fails, this is called a merge conflict. The conflict either manifests in textual merge conflicts where the merge fails to produce code, or semantic merge conflicts where the merged code results in compiler or test breaks. Resolving these conflicts for large code projects is expensive because it requires developers to manually identify the sources of conflict and correct them.

In this paper, we explore the feasibility of automatically repairing merge conflicts (both textual and semantic) using k-shot learning with large neural language models (LM) such as GPT-3. One of the challenges in leveraging such language models is to fit the examples and the queries within a small prompt (2048 tokens). We evaluate LMs and k-shot learning for two broad applications: (a) textual and semantic merge conflicts for a divergent fork Microsoft Edge, and (b) textual merge conflicts for a large number of JavaScript projects in GitHub. Our results are mixed: one one-hand, LMs provide the state-of-the-art (SOTA) performance on semantic merge conflict resolution for Edge compared to earlier symbolic approaches; on the other hand, LMs do not yet obviate the benefits of fine-tuning neural models (when sufficient data is available) or the design of special purpose domain-specific languages (DSL) for restricted patterns for program synthesis.

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1 INTRODUCTION

Merge conflicts today have been the common causes of broken pull requests, failure of continuous integration builds, and latent software defects in large projects [7]. One of the key reasons for the trends in issues caused by merge conflicts is the increasing collaborative environment in large modern software. A recent study showed that with thousands of people and tens of active branches committed to the same code base, nearly 20 percent of all the merge attempts in the large project finally ended with a bad merge [7].

A bad merge originates from either a textual merge conflict or a semantic merge conflict. A textual merge conflict occurs when two developers differently edit the same line of code. Normally, a developer then must resolve the conflict manually (i.e., when using git merge). In contrast, a semantic merge conflict occurs when there is no textual merge conflict but the merge results in a broken build, failing test (that would have otherwise passed), or unintended runtime behavior. Such semantic merge conflicts cannot be automatically resolved and thus require manual fixes from developers [17]. Such fixes greatly delay the development process.

Semantic merge conflicts can manifest in all forms of merge attempts, but we observed that they often appear in divergent forks. A divergent fork is created as a copy of the source repository without the intention to rarely (if ever) merge back. The standard terminology refers to the source repository as the upstream project and a fork is called the downstream project. Downstream has an independent development history which is rarely merged back to the upstream [17]. For example, Microsoft Edge, Opera and Brave are all based on the same upstream (Chromium). Each downstream branch periodically pulls the latest updates from upstream and merges them with other branches in the downstream repository. Using divergent forks saves a large amount of developer time by reusing functions and classes already defined and tested upstream, expedites the whole development process, and improves the maintainability of the code repository [17].

However, in a divergent fork, downstream developers frequently suffer from both textual and semantic merge conflicts. The reason is because upstream and downstream have an independent development processes with the downstream being out of sync with the upstream. Downstream developers often have little knowledge of current upstream updates. Taking Microsoft Edge as an example, a study showed that over a three-month period there were more than 25,000 upstream commits in Chromium and they all had to be merged downstream [17]. This level of merge frequency makes it difficult or even infeasible for downstream developers to inspect every upstream change before a merge.

Figure 1 illustrates an example of a semantic merge conflict. A function `foo()` was initially introduced upstream. After the original
fork, another function useFoo(), which invokes foo(), was created downstream. Concurrently, in the upstream branch the function foo() was renamed to bar(). Later, during the next pull from upstream, there was no textual merge conflict between two versions circled in red. The definition of foo() downstream did not change before the merge, so the merging algorithm simply renamed it into bar(). Thus, a semantic merge conflict is born, as foo() now has no definition in the downstream and will not compile.

The example in Fig. 1 is not artificially contrived: semantic merge conflicts happen daily in the Microsoft Edge development process. A snippet illustrating the root cause of one such conflict is given in Fig. 2. It is a fragment of the log of git diff applied to two commits in the upstream branch. The snippet shows that function IsIncognito() was renamed to GetIncognito(). After the merge, the downstream branch fails to compile with the message, "no member named IsIncognito() in BrowserView".

To help a programmer deal with build breaks caused by semantic merge conflicts, we developed a tool, named Gmerge, that automatically suggests merge conflict resolutions. Gmerge takes as input a merge conflict and merge histories from both upstream and downstream. Gmerge returns a conflict resolution which indicates which lines of code need to change, and how. In our particular Edge example, Gmerge returns the conflict resolution which is given in Fig. 3. It states that function IsIncognito() should be renamed to function GetIncognito().

The motivation for this work stems from the need to have a tool that helps programmers in repairing semantic merge conflicts in Microsoft Edge. Repairing semantic merge conflicts is prohibitively expensive for downstream developers. To find a root cause of the conflict, a developer needs to manually inspect the upstream commit history, which, for a large project, can be measured in thousands of commits. The previous study [17] have shown that through the course of three months around 800 commits were identified as attempts to solve merge conflicts. Each commit requires Edge developers additional time to resolve.

Our tool is based on k-shot learning with a large language model (GPT-3 [2]). GPT-3 is a large language model that has been successfully deployed in many applications such as questions answering [2], text completion, source code generation [4] and in many other fields. The biggest difference between GPT-3 and other supervised machine learning models is that the user does not need to train the model specifically for their application. The user only provides a few "shots" (or examples to prime the model) as input to GPT-3 and GPT-3 achieves competitive results, compared to other supervised machine learning models. A shot is a standard term that describes a question/answer pair. Motivated by GPT-3’s successful applications in other fields, this paper investigates using GPT-3 to resolve merge conflicts. A k-shot learning approach with GPT-3 provides a few "shots" (or examples to prime the model) as input to GPT-3 and GPT-3 achieves competitive results, compared to other supervised machine learning models. A k-shot learning implies we can use existing large language models and leverage them as they get better.

There are two main challenges with a k-shot approach: data curation and prompt engineering. Data curation automatically extracts source code changes related to merge conflicts. These changes are extracted from both upstream and downstream commits and they are converted into an intermediate representation (IR). Prompt engineering takes data in the IR format and translates the data into input
consumable by GPT-3. A key challenge with prompt engineering is that GPT-3’s input is limited to 2048 tokens and thus the shot and query must fit within it. To tackle this challenge, Gmerge applies string pattern analysis and heuristics in prompt engineering.

Finally, to empirically evaluate our approach, we have run Gmerge on real-world Microsoft Edge semantic merge conflicts. Our evaluation shows (we use the developer’s actual fixes as the ground truth), Gmerge learns the correct resolutions at the state-of-the-art (SOTA) 64.6% of accuracy. Our evaluation demonstrates the effectiveness of k-shot learning, which provides a cost-effective and language-agnostic solution for real-world semantic merge conflicts.

We then generalize our approach to textual merge conflicts and evaluate the effectiveness of our data curation and prompt engineering in this domain on two case studies (the first based on program synthesis and the second based on fine-tuning large scale language models). Both of these existing tools require significant engineering while a k-shot approach is relatively simpler. In the first, we show k-shot learning has performance on par with current SOTA tools, while in the second, SOTA tools significantly outperform Gmerge. However, note that in both case studies, the current SOTA approaches require special purpose domain-specific languages (DSL) for program synthesis or fine-tuned machine learning models. When we compare the performance Gmerge and those tools without fine-tuning, Gmerge outperforms them.

In summary, we make the following contributions:

- We present a data-driven tool Gmerge that uses k-shot learning with a large language model (GPT-3) to automatically find repairs for merge conflicts.
- We propose a method of prompt engineering that translates merge conflict examples and queries to a small prompt for GPT-3.
- We perform an evaluation of Gmerge on both textual and semantic real-world merge conflicts problems. We obtained the state-of-the-art (SOTA) performance on semantic merge conflict resolution for a divergent fork, and comparable performance on textual merge conflicts problems including divergent forks and a large number of JavaScript projects in GitHub.

2 SYSTEM OVERVIEW

The overview of the Gmerge tool is shown in Fig. 4. It takes as input three parameters: a merge conflict, and commits in the upstream and downstream repositories that constitute the merge. As output, Gmerge returns a merge conflict resolution.

Gmerge contains two main modules: data curation and prompt engineering.

The data curation module takes as input the upstream and downstream commit logs along with the downstream semantic merge conflict including the compiler error messages. It generates JSON files as the intermediate representation (IR) for the prompt engineering module. We call this file a conflict description. This file contains three case studies, but data curation is extensively used only in the first case study. However, when we run Gmerge on an existing benchmark where the conflicts have already been curated, Gmerge skips this module and directly goes to the next module.

The purpose of the prompt engineering module is to translate a conflict description file into the small prompt format required as input for GPT-3. The prompt engineering is a technical module and for each of our case studies we needed to apply various different heuristics, described in more details in Sections 3.2 and 4. This is due to the fact that conflict description files for each case study have different format.

In the next two sections, we describe how we apply Gmerge to different merge conflict case studies.

3 CASE STUDY 1: RESOLVING SEMANTIC MERGE CONFLICTS FOR A DIVERGENT FORK

3.1 Data Collection and Curation

Merge conflicts in downstream forks are often introduced by commits made in upstream repository, so the goal of the data collection and curation process is to identify and extract all the source code changes in upstream that are related to the given merge conflict. In real-world software development, this is also the first step that the programmer manually performs in trying to resolve a failed merge. For large upstream repositories such as Chromium (of which Microsoft Edge is a downstream divergent fork), searching through the thousands of upstream commits is a tedious and error-prone task. In Gmerge we automate this whole process.

Gmerge takes the commit logs of the repository, the semantic merge conflicts including the compiler error messages as the inputs, and outputs a JSON file for each semantic merge conflict. This JSON file contains all code-level changes relevant to the target merge conflict. The files are designed to be self-contained, in the sense that it is sufficient to check the JSON file to gain all the information relevant for the given semantic merge conflicts. Each file has three key components: 1) the set of relevant changes from upstream, 2) the conflict to be fixed in downstream, and 3) the resolution provided by the real-world developers. The third component is only relevant for establishing the ground-truth for our evaluation.

To evaluate how accurate are conflict resolutions suggested by Gmerge, we evaluated it on existing semantic merge conflicts. We store the manual repair so that we can compare it to our derived solution.

Fig. 5 shows an example JSON file that Gmerge generated for the merge conflict given in Fig. 2 and Fig. 3. In Fig. 5, line 2 to line 12 are the relevant changes from upstream. Line 13 is the merge conflict and line 14 is the resolution provided by the Edge developers.

Semantic merge conflicts happen when the code produced by a merge (either through the textual merge or through a user resolution) cannot be compiled; the compiler fails to produce the executable code and outputs an error message. We use this error
In our application, we use shots to let the GPT-3 model better understand how the merge conflict is solved and what the ideal resolution looks like. Fig. 7 is the real-world example on how we use GMerge to resolve the merge conflict in Fig. 3.

Figure 7: An Example of merge conflict resolution using one shot learning in GPT-3. The shot is represented in line 1 to line 8. The query starts from line 10 and it ends at line 17. The line 20 is not in the prompt, and it is the output of GPT-3 model for the resolution of the merge conflict.

**Prompt Format** In the prompt, the lines start with a double -- and ++ represent the conflict related changes in upstream. The line starting with a single - appears only at the end of the query and it represents the merge conflict in downstream. The line starting with a single + is not in the prompt. Instead, it is the output of GPT-3 for the resolution of the merge conflict.

**Prompt Content** GPT-3 has a fixed input size, 2048 tokens. This is in sharp contrast to the massive code diffs of thousands of commits.

3.2 Prompt Engineering

The prompt engineering module applies various heuristics on the JSON representation of the conflicts to translate merge conflict examples and queries to succinct prompts for GPT-3. The output of GPT-3 is the resolution of the merge conflict.

**Prompt Structure** Each prompt is a question to GPT-3 and it has two parts: shots and one query. The first part, the shots is optional in the prompt. If the prompt contains no shot, it is called zero-shot learning.

Each shot itself is an example of how a previous merge conflict is resolved. We use shots to provide a context to GPT-3 about the current task, and provide an example of what should be the correct form of the output. Fig. 6 shows an example of one shot learning. By providing an example to GPT-3, the model learns the relation between apple to red, and then applies the relation to the eggplant, and outputs purple as the result.

Figure 6: An Example of one shot learning in GPT-3. The output of this example by GPT-3 is Purple. Line 1 and line 2 are the shot. Line 4 is the query.
A single JSON file could contain thousands of lines of code changes related to a merge conflict. To leverage the power of GPT-3, one of the key challenges in Gmerge is to fit the examples and the queries into this small prompt.

We adopt a heuristic to ensure that we have prioritize diverse representation of “UpsteamChanges” (in the JSON file) in the prompt. Our intuition is that we want each pair of “UpsteamChanges” has distinct string edit sequence. Each edit sequence is a list of operations that are applied to strings. Applying the edit sequence on the first string produces the second one. There are three operations in the edit, the addition +, the deletion - or the equivalence =. For any string character replacement, we used → to represent it. We also omit the space padding in our edit sequence definition.

We use the Python library `difflib` to compute the string difference. For simplicity, if any two adjacent characters have the same operation, we will only keep one operation in the final edit sequence. For example, given line 14 and line 15 as the input, the edit sequence is =→. Gmerge makes sure that every -- and ++ string pairs in the prompt has a distinct edit sequence pattern. In this way, we managed to fit all the shots and the queries into the small prompt (2048 tokens). In Sec. 3.3, we demonstrate the effectiveness of our prompt content design.

### 3.3 Evaluation

We evaluate the efficacy of Gmerge on semantic merge conflicts by answering the following questions:

1. Can Gmerge resolve semantic merge conflicts in divergent forks?
2. Does prompt engineering positively affects the accuracy?
3. Are larger language models more accurate than smaller ones?

**Experiment Setup** We collected Edge merge conflicts from Aug 2020 to April 2021. We used four clang compiler error types to collect those conflicts that are related to the semantic merge conflict. These four error types are `err_no_member`, `err_no_member_suggest`, `err_undeclared_var_use_suggest` and `err_undeclared_use_suggest`. We obtained a total of 379 semantic merge conflicts for our empirical evaluation. Each conflict is prepossessed into a JSON file format.

The evaluation metric in Gmerge is that if the actual fix by users is a prefix of our generated resolution, we consider this resolution is correct. We take this evaluation metric because GPT-3 is an autoregressive model, which sometimes outputs the string without a stop unless the output reaches a fixed length. In addition, an actual user fix could cross multiple lines. In Gmerge, we extracted only the first line as the user fix. Therefore, we required the actual fix by users should be the prefix of our resolution.

This evaluation metric is considered a conservative one because there might exist multiple correct ways for users to fix a merge conflict. All experiments were conducted on a Windows computer with an Intel i7 CPU and 48 GB of RAM.

**Can Gmerge resolve semantic merge conflicts in divergent forks?** Table 1 shows the performance of Gmerge on our dataset. Gmerge has an overall accuracy of 64.6% after ten model trials. Table 1 also includes a comparison of Gmerge to three baselines. We first compared Gmerge to a heuristic-based approach, StringMerge. And then, we compared Gmerge to the state-of-the-art string-based program synthesis approach [18], Transformation.Text. And then we evaluated how the choices of language model (GPT-3 and GPT-J) affected the results.

Our first baseline Stringmerge, is a heuristic-based approach designed by empirically analyzing patterns in semantic merge conflicts for a divergent fork. For each before-after code change pair, Stringmerge computes the patterns of string diff character by character. Then it applies the learned pattern in downstream to generate a fix. It mimics the way Edge developers manually fix such a merge conflict in the real world. Table 1 shows Stringmerge’s performance. Gmerge performs better in terms of resolution accuracy (64.6% vs 30.1%).

Our second baseline is the state-of-the-art program synthesis approach on string transformation [18]. Gmerge performs much better in terms of resolution accuracy (64.6% vs 25.9%) and surprisingly even the heuristic-based Stringmerge outperforms it. One possible reason is that Transformation.Text is a generic string transformation tool, so the pattern in semantic merge conflict resolution is too complex for Transformation.Text to learn. Fig. 11 is such a challenging example that is difficult for the existing program synthesis approach to resolve.

Our third baseline Gmerge (GPT-J) is introduced to evaluate how the size of the language model affects the result. GPT-3 and GPT-J have similar architectures, but GPT-3 has 175 billion parameters while GPT-J has 6 billion. Our evaluation shows that the size of the model affects the ability to resolve semantic merge conflicts. Gmerge performs much better than Gmerge (GPT-J) in terms of resolution accuracy (64.6% vs 39.1%) Gmerge (GPT-J) has performed better than our heuristic based approach Stringmerge and Transformation.Text. This shows that resolving semantic merge conflicts is a non-trivial problem, and a large language model is able to automatically generate a resolution for semantic merge conflicts with high accuracy.

**Does prompt engineering positively affects the accuracy?** Table 2 shows how prompt engineering affects the accuracy of merge conflict resolution in Gmerge. One of the advantages of GPT-3 is that it only needs a few examples (shots) as the input. We evaluated Gmerge in two prompt structures: one shot and zero shot.

One of the major technical challenges in Gmerge is to fit the shot and the query into the prompt in GPT-3, we have evaluated Gmerge on three different prompt structures in Table 2. “First pair” means that we only choose the first conflict related source code change in the JSON file to form the query. “Maximal Test (without heuristics)”
takes as many changes as possible in the original sequence until the size of the prompt becomes larger than 2048 tokens. “Maximal Test (with heuristics)” takes the heuristics described in Sec. 3.2 as the filtering method to prioritize some changes in the prompt.

The evaluation shows that having a shot as the input to the language model significantly improves the results in all prompt structures. This meets our expectation because having a shot not only clearly pinpoints the current task to the model but also provides an example of what is the expected output from the model. Moreover, the evaluation shows that providing more conflicts related code changes as the context improves the accuracy of the model. It further shows that with the heuristics, Gmerge achieved the highest accuracy of 64.6%.

GPT-3 and GPT-J each output one resolution at one model trial. In our experiment, we repeatedly query GPT-3, and if the resolution is produced in any of the trials, we mark the merge conflict as “resolved”. We evaluated how the number of trials affect the model accuracy. Fig. 8 shows that the overall accuracy of GPT-3 and GPT-J both increased with the number of model trials. For example, for GPT-3, ten independent trials achieves the accuracy of 64.6% in contrast to the accuracy of 37.2% with only one trial. Compared to the GPT-3 model, we only observed a modest accuracy gain in the GPT-J model. StringMerge and Transformation.Text have no accuracy gain because they produce a deterministic result in every run.

**Are larger language models more accurate than smaller ones?**

One benefit of Gmerge is that its k-shot approach does not require expensive task specific fine-tuning. Thus, Gmerge can benefit from large scale language autoregressive models. In this section, we demonstrate that the size of the model has a significant impact on Gmerge’s task specific accuracy. Fig. 8 shows that the overall accuracy of GPT-3 increased more sharply than GPT-J with the increase of model queries. Approximately 30% of the additional merge conflicts are resolved if we query the GPT-3 model multiple times. In contrast, for GPT-J, only 5% of the additional merge conflicts can be resolved in this setting.

Based on what we observed from the result, we come up with the following interesting hypothesis: Given a merge conflict, GPT-J is likely to have a resolving probability close to zero (non-solvable) or close to one (definitely solvable). In other words, the density of the merge conflicts, which can be resolved after several model trials, is much higher in GPT-3 than GPT-J.

To validate this hypothesis, for both GPT-3 and GPT-J, our goal is to use a high degree polynomial function to continuously model the probability density of the samples in terms of different conflict resolving probabilities. We specifically focused on the proportion of samples that have resolving probability close to zero (non-solvable) or close to one (definitely solvable). We used the gradient descent algorithm [12] to minimize the loss function in our training. The loss function was computed by the sum of the squared errors in our setting.

With our learned probability density function, we simulated the accuracy graph of the first twenty trials of the GPT-3 and the GPT-J respectively to see how our simulated graph fits the observed results. Fig. 9 shows that our function closely fits our observed results.

### 3.4 A Challenging Example Resolved by Gmerge

In this subsection, we illustrate the complexity of real-world merge conflicts that downstream developers face in daily development. We closely inspect the example of a broken build taken from the Edge repository. For example, in Fig. 10, the compiler error message only indicated that it could not find a definition for PermissionRequestType.

The correct resolution to this particular problem is given the line annotated with + in Fig. 10. This was a repair that the developer has committed.

```plaintext
1  - PermissionRequestType::PERMISSION_CAMERA_PAN_TILT_ZOOM:
2     + RequestType::kCameraPanTiltZoom:
```

![Figure 10: A solution for the challenging semantic merge conflict resolution in Edge downstream.](image-url)
To correctly resolve such a merge conflict, developers need to learn how the upstream context changed and then apply the similar changes to the downstream context. To derive this particular resolution, it was not enough to find the relevant file in the commit history and then propagate the changes: the developer needed to find three different files and manually combine the changes described in those files to derive the required resolution. We list the most relevant changes in Fig. 11.

![Figure 11: Root cause of a challenging semantic merge conflict in Chromium upstream.](image)

The developers first detected that the root cause of this compiler error was due to fact that PermissionRequestType has been renamed to RequestType in upstream. However, applying these changes to the PermissionRequestType downstream still did not resolve this merge conflict. This was due to the fact that PERMISSION_NOTIFICATIONS in upstream was changed to kNotifications. After the developer learned how the upstream context changed and applied similar changes to the downstream context, the semantic merge conflict is resolved by changing PERMISSION_NOTIFICATIONS to kNotifications.

The existing merge conflict resolution approaches [11, 17, 18] are not helpful in such cases, because their learning algorithms are limited when it comes to learning and combining complex string transformation. Indeed, in our empirical evaluation, given in Sec. 3.3, we show that none of our baseline methods could resolve this merge conflict. With the prompt shown in Fig. 12, GMERGE generated line 25 as the resolution to this conflict.

### 3.5 Discussion

**Automation Level** The closest existing work to GMERGE is the MrgBldBrkFixer [17], which investigated the feasibility of automatically fixing the semantic merge conflicts in Microsoft Edge. It computes the differences of Abstract Syntax Trees (ASTs) of the two programs to identify the changes in upstream for a given symbol and then applies such a patch on the conflict in downstream for a fix.

However, MrgBldBrkFixer is not fully automated, contrary to GMERGE. It needs downstream developers to manually classify the semantic conflicts and assigns type for these conflicts. Therefore, MrgBldBrkFixer still requires manual labor in resolving merge conflicts. This is the reason why we cannot use MrgBldBrkFixer as the baseline in our evaluation.

Automation is important in resolving semantic merge conflicts for a divergent fork because the motivation of our work is that it often costs developers much time to manually identify the source of conflicts and correct them.

### 3.6 Threats to Validity

GMERGE cannot provide any guarantee to the resolution of merge conflicts. GMERGE relied on Clang compiler message to locate the conflict related changes in upstream. Therefore, if the compiler

![Figure 12: A challenging merge conflict example resolved by GMERGE. Line 1 to line 8 are the shot, line 10 to line 22 are the query to GPT-3.](image)

Is GPT-3 able to generate out-of-vocabulary resolution for semantic merge conflicts? If the resolution of the conflict contains a token that is not contained in the prompt, it is an out-of-vocabulary resolution. It is difficult even for experienced developers to obtain such an out-of-vocabulary resolution. We then automatically check how many times the actual resolution contains tokens that are not in the prompt.

We found that 286 out of 379 cases, the resolution is in the vocabulary of the given prompt. GPT-3 gets the answer for 221 of them with 77.3% accuracy.

Surprisingly, for the rest of 93 examples, GPT-3 gets 14 correct resolutions (15.1%) Fig. 12 is such an example. The details of our result is in Table 3, which shows GPT-3 is able to generate complex merge conflict resolutions.

### Table 3: GMERGE generates resolution even if the resolution contains a token that is out of the input vocabulary.

| Tokens Out of Vocabulary | GMERGE resolved the conflict | Occurrences |
|--------------------------|-----------------------------|-------------|
| Not Required             | Yes                         | 221         |
| Required                 | No                          | 65          |
| Required                 | Yes                         | 14          |
| Required                 | No                          | 79          |

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fails to pinpoint where the error is or the git commit history is not accurate, Gmerge cannot handle such merge conflicts.

Gmerge cannot resolve such a merge conflict that is resolved by simply deleting the line that contains merge conflict. Based on our expertise, this is a rare case in day to day development in a divergent fork, and should not be recommended in the standard practice.

### 4 GENERALIZATION GMERGE ON TEXTUAL MERGE CONFLICTS

To generalize Gmerge to resolving textual merge conflicts, we conducted two case studies, 1) textual merge conflicts for the divergent fork Microsoft Edge, and 2) textual merge conflicts for a large number of JavaScript projects in GitHub. In both studies, the repositories that contain the merge conflicts are not available directly in the benchmark, thus making Gmerge infeasible to do the data curation. We run Gmerge on the two existing benchmarks [6, 11] to resolve merge conflicts using only the prompt engineering module.

#### 4.1 Case study 2: Gmerge on resolving textual merge conflicts for a divergent fork

**Textual Merge Conflict** Fig. 13 shows an example of a real-world textual merge conflict in Edge development. The conflict is caused by the header file url_utils.h in the forked branch that is an alternate version of the header file google_utils.h in the main branch. To resolve this issue, downstream developers kept the one in the forked branch and excluded the one in the main branch. Running Gmerge on this example will automatically produce the same resolution.

![Example of Prompt in Textual Merge Conflict Resolution by Gmerge](image)

**Figure 13:** A challenging example for resolving a textual merge conflict for a divergent fork. The line that starts with a "-" means this line is removed from the final merged code. The line that starts with a "+" means this line is kept in the final merged code.

**Benchmark Description** The problem of textual merge conflict resolution for header files and Macro in large projects has been studied in the paper [11] and the benchmark is publicly available. For each merge conflict in the benchmark, it shows how a textual merge conflict is resolved in Microsoft Edge development. Each conflict is either a C++ header file conflict or a Macro related conflict, and the size of the merge conflict has up to two lines of changes. This benchmark is collected from Microsoft Edge development repository in an eight-week period (March 30 2020 to April 24, 2020). In total, this benchmark has 122 textual merge conflicts due to header file conflicts and 38 conflicts due to Macro conflicts.

**Prompt Engineering** We use the same prompt structure as in prior case studies. However, without the assistance of data curation module, in this case study, we can only pick the examples in the existing benchmark to form the shots and use each of unused examples as query to evaluate Gmerge.

We have two prompt engineering methods here. First, we randomly select a few examples from each category to form the shot. We ended up with five header file examples and two Macro examples in the shot. We name this prompt engineering method as the "Randomly selected shots". Second, we use our domain specific knowledge to pick two typical examples as the shot. We name this prompt engineering method as the "Representative shots".

![Example of Prompt in Textual Merge Conflict Resolution by Gmerge](image)

**Figure 14:** An Example of Prompt in Textual Merge Conflict Resolution by Gmerge

For example, in Fig. 14, line 1 to line 10 is our shot, which has two header file merge conflicts and their resolutions. Our target conflict is shown from line 23 to line 28. By feeding the shot to the GPT-3 model, it outputs:

```cpp
#include "build/build_config.h"
#include "media/media_buildflags.h"
```

and this is the exact resolution provided by the Edge developers.

**Evaluation and Discussion** Table 4 shows the accuracy of resolution on Edge header file and Macro textual merge conflict dataset. Compared to the existing work, which requires a careful design of domain specific language, our tool Gmerge has better accuracy on Macro related textual merge conflicts. For header file related merge conflicts, Gmerge has a modest accuracy of 60.0%. This is mainly...
Can Pre-trained Language Models be Used to Resolve Textual and Semantic Merge Conflicts?

**Table 4: Merge conflict resolving accuracy for Gmerge on Edge header file and Macro textual merge conflict dataset.**

|                | SOTA [12] | Randomly Selected Shots | Representative Shots |
|----------------|-----------|-------------------------|----------------------|
| Header File    | 91.8% (121/122) | 49.6% (58/117) | 60.0% (72/120) |
| Macro          | 94.4% (35/38)     | 100% (36/36)     | 100% (36/36)     |

**Table 5: A merge conflict instance in the Deepmerge benchmark [6].** Variant A and B are two versions of code changed from Base O. Resolution R is the fix provided by the developers. Merge size is computed by adding the lines of A and B.

| Base O         | Variant A | Variant B | Resolution R |
|----------------|-----------|-----------|---------------|
| (base.js)      | (a.js)    | (b.js)    | (r.js)        |
| var b = 5.7;   | let b = x + 5.7; | var y = floor(b); | var y = floor(x + 5.7); |
| var y = floor(b); | console.log(y); | var y = floor(x + 5.7); | console.log(y); |

because Gmerge does not have the domain specific knowledge for the repository in the input, which is used to resolve header file related merge conflicts. Fig. 15 is such an example that can only be resolved by using prior domain specific knowledge.

**Figure 15: A merge conflict that cannot be resolved without prior repository domain specific knowledge.** The “base/logging.h” should always be removed from the forked branch because the forked branch, Microsoft Edge uses a different logging system.

To resolve such a merge conflict, the existing solution [11] crafted a new domain-specific language that captures the patterns from historical data as resolution strategies, and used program synthesis to learn such repeated resolutions. Applying the learned strategies to the new unseen merge conflicts will automatically synthesize a resolution. However, without access to the historical data of the full repository, the following “always deleting logging.h this pattern cannot be inferred by Gmerge.”

**4.2 Case study 3: Gmerge on textual merge conflicts for a large number of JavaScript projects in GitHub.**

Gmerge is not just limited to divergent fork development infrastructure. In this section, we evaluate Gmerge to resolve textual merge conflicts collected over a large collection of open-source GitHub repositories.

We evaluated Gmerge on an existing Javascript merge conflicts benchmark used in DeepMerge [6].

**Benchmark Description** This benchmark [6] contains thousands of real-world textual merge conflict examples collected from Github.

**Table 6: Merge Conflict Resolving Accuracy for Gmerge on Deepmerge [6] Dataset.** The first row is the input size of the merge. The prompt format that Gmerge uses is on a par with the naive input representation for Deepmerge.

|                | [0,3] lines | [3,5] lines | [5,7] lines | [7,10] lines | [>10] lines | Overall |
|----------------|-------------|-------------|-------------|-------------|-------------|---------|
| Gmerge (conflict) | 32.11%     | 17.52%     | 12.46%     | 10.2%      | 4.46%       | 15.02%  |
| Gmerge (tuple)   | 29.1%      | 14.9%      | 12.46%     | 10.2%      | 2.48%       | 11.99%  |
| Deepmerge (Top 3, naive) | N/A      | N/A        | N/A        | N/A        | N/A        | N/A    |
| Deepmerge (Top 3, random) | 75.4%   | 56.10%    | 37.04%     | 18.87%     | 2.95%       | 30.05%  |

Table 5 shows such an example. Resolving merge conflicts in this benchmark is challenging because the conflicts 1) are collected from various open-source repositories other than a single repository as in the case of Edge, so the benchmark contains more generic code patterns and 2) vary in terms of their merge sizes. Some examples have large merge size up to hundreds of lines.

**Prompt Engineering** Similar to case study 2, without the assistance of the data curation module, we picked the examples in the existing benchmark to form the shots, and used the rest of the examples as queries to evaluate Gmerge.

For this case study, we chose the same shot content but with different shot formats. We adopted two formats of shot designs shown in Fig. 16. Our goal is to check that if using different shot formats improves the final resolution accuracy.

**Listing 1: Classic Conflict**

```javascript
1 Questions: 1 Questions: 
2 <<<<<<<<<<< 2 a.js: 
3 let b = x + 5.7; let b = x + 5.7
4 var y = floor(b); var y = floor(b)
5 console.log(y); console.log(y)
6 | | | | 6 base.js:
7 var b = 5.7; var b = 5.7; 
8 var y = floor(b); var y = floor(b); 
9 ======== 9 b.js: 
10 var y = floor(x + 5.7); 10 var y = floor(x + 5.7); 
11 11 11 
12 12 12 
13 Answers: 13 Answers: 
14 var y = floor(x + 5.7); 14 var y = floor(x + 5.7); 
15 console.log(y); 15 console.log(y);
```

**Figure 16: Two formats of shot designs.**

**Evaluation and Discussion** Compared to the state-of-the-art [6], Gmerge has a suboptimal performance when the input merge size is small (less than eight lines). However, when the input size is large (greater than eight lines), Gmerge outperformed the SOTA.

Deepmerge is known to be sensitive to the input merge conflict size as it performs better in small merges. This is possible because the input to the model is carefully tuned and it is represented token by token. Instead, in Gmerge, the input is aligned in a sequence of variant A, variant B and base O and fed into the language model all at once. This way of combining the inputs of A, B and O is termed as naive in DeepMerge. When using the same input representation, Gmerge is slightly outperformed (15.02% vs 14.09%) the Deepmerge model.
In addition, using the classic conflict formulation in the prompt improve the result by 25% (11.99% vs 15.02%). This result shows that having the right prompt format improves the resolution accuracy.

4.3 Discussion
In summary, these two case studies show that Gmerge has modest to competitive performance on problems where current SOTA approaches require special-purpose domain specific languages (DSL) for program synthesis or fine-tuning a neural network model (that requires tens of thousands of data points). It highlights that language models still do not obviate the need for domain-specific investments for the merge conflict problem. Further, even when the data curation is not feasible due to the lack of repository information, prompt engineering is still useful to improve the accuracy of the resolution in Gmerge.

5 RELATED WORK

Semantics Merge Conflict Semantics merge conflicts happen when the merged code cannot be successfully compiled. This problem was first introduced by Horwitz et al. [9] and later formalized by Yang et al. [9] in 1990s. A recent study [5, 7] has shown that having such a bad merge in the code delayed the development cycle or caused damage by simply leaving bugs in the code. As a result, semantics merge conflict detection [16] and resolution approaches [14, 17] have been proposed. JDME [1] automatically tunes a semi-structured merge based conflict locations detection and resolution. NLX_REG [13] uses large language model to synthesizing regular expressions. SAFEMERGE [16] prevent merge conflicts by defining formal specifications to the based code, variants of the code and the final merged code. However, it did not directly produce the merge conflict resolutions as Gmerge does.

The closest work to ours is the MrghdlBrkFixer [17]. It resolves semantics merge conflict for a divergent fork by analyzing the AST diffs in changes in the upstream to construct a patch for merge conflicts. However, MrghdlBrkFixer still requires developers’ manual work to classify the build breaks, and the tool heavily relies on the AST analysis for C++ code only. In contrast, Gmerge is scalable, fully automated and language-agnostic by leveraging large scale language models.

Textual Merge Conflict Textual merge conflicts have been long known as a severe and challenging problem, as reported in prior studies [7, 11]. As a result, textual merge conflict mining and detection approaches [1, 3, 8, 10] have been proposed. Going one step further than bad merge prevention, to directly resolve the merge conflict, recently, we have witnessed great progress via program synthesis [11] and machine learning [6]. Deepmerge [6] required customized machine learning models. Pan et al. [11] studied the historical data of bad merge to design special purpose domain-specific languages (DSL) for program synthesis. IntelliMerge [15] studied refactoring caused merge conflicts in software development and evolution in Java programs.

6 CONCLUSION
In this paper, we explored the feasibility of leveraging k-shot learning with large language models for resolving various merge conflicts (both textual and semantic). Our results demonstrate that LMs have the potential to be useful for this important problem in software engineering by providing cost-effective solutions ranging from SOTA performance on some domains (e.g. in semantic merge conflicts in Edge), while providing modest performance (on textual conflicts) on other domains. Our work also illustrates the importance of prompt engineering for these language models as an important avenue for research, including automating the most effective prompts given data from a domain.

In future work, we are working on feeding more structured and merge-aware representation of inputs in the prompts to better communicate the problem to the LMs. For instance, one can perform an edit-aware encoding of the merge input as done in DeepMerge, or encode semantics of pointer networks to only rearrange lines of the code and the final merged code. However, it did not directly produce the merge conflict resolutions as Gmerge does.

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