# Migrating Code At Scale With LLMs At Google

Celal Ziftci\* celal@google.com Google New York, NY, USA

Bo Kim\* bohyungk@google.com Google New York, NY, USA Stoyan Nikolov\* stoyannk@google.com Google Munich, Germany

Daniele Codecasa\*
cdcs@google.com
Google
Munich, Germany

Anna Sjövall\*
annaps@google.com
Google
Munich, Germany

Max Kim\*
maxkim@google.com
Google
Mountain View, CA, USA

## Abstract

Developers often evolve an existing software system by making internal changes, called *migration*. Moving to a new framework, changing implementation to improve efficiency, and upgrading a dependency to its latest version are examples of migrations.

Migration is a common and typically continuous maintenance task undertaken either manually or through tooling. Certain migrations are labor intensive and costly, developers do not find the required work rewarding, and they may take years to complete. Hence, automation is preferred for such migrations.

In this paper, we discuss a large-scale, costly and traditionally manual migration project at Google, propose a novel automated algorithm that uses change location discovery and a Large Language Model (LLM) to aid developers conduct the migration, report the results of a large case study, and discuss lessons learned.

Our case study on 39 distinct migrations undertaken by three developers over twelve months shows that a total of 595 code changes with 93, 574 edits have been submitted, where 74.45% of the code changes and 69.46% of the edits were generated by the LLM. The developers reported high satisfaction with the automated tooling, and estimated a 50% reduction on the total time spent on the migration compared to earlier manual migrations.

Our results suggest that our automated, LLM-assisted workflow can serve as a model for similar initiatives.

## **CCS Concepts**

• Software and its engineering  $\rightarrow$  Very high level languages; Software maintenance tools; • Computing methodologies  $\rightarrow$  Natural language generation.

#### **Keywords**

Software, Migration, Refactoring, Transformation, Productivity, LLM  $\,$ 

# **Preprint Notice**

This is a preprint of a paper accepted at the ACM International Conference on the Foundations of Software Engineering (FSE) 2025.

#### 1 Introduction

Migration is a crucial process in software development that involves modernizing and adapting systems to ensure ongoing functionality and compatibility. This may include, but is not limited to, updating or restructuring existing code, improving its organization, making it easier to understand and maintain, transitioning to newer versions of programming languages to leverage new features and address potential security vulnerabilities, updating dependencies such as APIs and libraries to modernize the codebase, fix bugs and improve performance, and adapting to changes in underlying frameworks and platforms that applications depend on.

Performing such changes manually, particularly in large codebases, is often tedious, time-consuming, and error-prone, especially when dealing with complex code structures and dependencies, resulting in barriers for developers [26, 36, 68]. As a result, automating code migrations is critical in maintaining systems to avoid recurring manual work, since systems typically undergo several migrations over their lifetime.

Migrations are typically automated using different techniques, ranging from regular expression search and replace, to using code transformation tools, to specialized domain specific tooling. Existing techniques have shortcomings in their accuracy on finding relevant locations to change and the need for maintenance of the rules or the domain specific tools.

Recently, the introduction of Large Language Models (LLMs) created opportunities to support several software engineering tasks, including generating tests [6, 59, 61], code refactoring [60], documentation generation [17], bug detection [5], fault localization [31], fixing bugs [62], code reviews [65, 66], pair programming [28], and recently migrations [4, 48].

In this paper, we discuss an automated solution for a large, costly migration at Google on modifying 32-bit integers to 64-bits by automatically identifying areas of code that require modification, using LLMs to obtain the necessary code changes, running several forms of validation to confirm that the code changes are valid, and sending the changes to developers for verification and acceptance to enable more efficient, reliable and verifiable code migrations that use natural language to describe the migration.

To the best of our knowledge, our work is the largest, most comprehensive code migration study using LLMs to date. We assess the success of our solution on 39 instances of this migration undertaken over twelve months, and report our learnings on the experiences of the three developers that conducted the migrations.

<sup>\*</sup>All authors contributed equally to this research.

```
// A toy type known to our systems
message Toy {
  int32 toy_id;
  uint32 price; // In US dollars
  bool in_inventory;
```

Listing 1: Example proto schema to describe toys in a toy store's inventory.

## 2 Migrating Identifiers From 32-bits To 64-bits

In this section, we discuss the specific type of migration we conducted at Google, its various characteristics, and show-case such a migration on an example.

# 2.1 Motivating Example

At Google, a typical way to describe the inputs and outputs of a system is to use a protocol buffer [67], *proto* in short, a structured data format that supports a wide range of scalar value types including enums, strings, integers and floating point numbers, as well as custom user-defined structured message formats built upon those scalar value types. Based on the proto definition, the compiler generates standardized library code in the user's target programming language of choice to manipulate instances of the proto.

Consider the proto schema in Listing 1 that describes different types of toys in an online toy store's inventory. Toy is a user-defined message type that contains three scalar fields: toy\_id is a 32 bit integer to uniquely identify a toy, price is a number that represents the price of the toy in US dollars, and in\_inventory is a boolean that represents whether a toy is currently in the store's inventory.

The system's inventory stores such proto instances in a database to show toy listings on a website. The system codebase in Java has references to the fields defined in the proto schema, with sample snippets shown in Listing 2 where there is a view that shows the toy with a different badge depending on when it was produced, and a test class with two test methods testing the view for toys that are produced before and after 2024.

Note that there are direct and indirect references to toy\_id in Listing 2. Lines 5, 13, 27, 39 are direct references, since they directly refer to the access methods for toy\_id in the proto, while lines 36 and 37 are indirect references, since they do not directly refer to toy\_id but contribute to the value used in the direct reference on line 39 through data flow.

Each toy in the system has a unique toy\_id, which we call ID interchangeably in the rest of this paper. Over time, as the number of toys in the system grows, there is a risk of running out of IDs for new toys since the maximum int32 is 2147483647. To mitigate this risk, the type of toy\_id in the proto schema can be changed in-place from int32 to int64 shown in Listing 3.

To be able to compile the code, this schema change first requires potential changes across the codebase everywhere toy\_id is directly or indirectly referenced, e.g. line 5 in Listing 2. Additionally, for the code to properly handle int64 values, line 13 needs to be updated to use 63 instead of 31. Finally, to ensure that the codebase properly works with int64 values instead of int32, it is a good idea to use large values (e.g. 1230000000000L) that exceed the maximum

```
/* ToyView.java */
1 final class TovView {
       public static HtmlView showToy(Toy toy) {
3
           if (toyIsProducedAfter2024(toy)) {
4
               // Create panel with "new" badge
5
               final int toyId = toy.getToyId();
6
               // Return the default panel
9
           }
10
       }
11
       static boolean toyIsProducedAfter2024(Toy toy) {
12
13
           return firstBitIsOne(toy.getToyId(), 31));
14
15
       // First ID bit is 1 if produced after 2024
17
       static boolean firstBitIsOne(long id, int shift) {
           return (id >> shift) == 1;
18
19
20 }
22 final class ToyViewTest {
                                 /* ToyViewTest.java */
     private static final Random R = new Random():
24
     public static int testShowToy_producedBefore2024() {
25
26
       final Toy testToy = Toy.Builder
27
                                .setToyId(-5)
28
                                .setPrice(12)
29
                                .IsInInventory(true).build();
30
       final HtmlView view = ToyView.showToy(testToy);
31
       // Assert that view has toy panel with "new" badge
32
33
     }
     public static int testShowToy_producedAfter2024() {
       final int randomId = R.nextInt(0, 100);
36
37
       final int toyId = randomId * 10;
       final Toy testToy = Toy.Builder
39
                                .setToyId(toyId)
40
                                .setPrice(23)
                                .IsInInventory(false).build()
       final HtmlView view = ToyView.showToy(testToy);
43
       // Assert that view has default panel
44
45
    }
```

Listing 2: Example code and tests in Java that references various fields of the proto schema.

int 32 value in our tests, i.e. modifications to lines 27, 36, 37 in Listing 2.

#### 2.2 Manual Migration

An instance of this migration for a specific ID has been undertaken at Google three years ago, where developers used regular expressions, *regex* for short, such as setToyId, getToyId, set\_toy\_id, get\_toy\_id to find references to a specific ID field in a proto in the entire codebase for several programming languages including Java,

```
// A toy type known to our systems
message Toy {
  int64 toy_id; // **Changed to int64**
  uint32 price; // In US dollars
  bool in_inventory;
}
```

Listing 3: Working example proto schema with toy\_id now int64.

C++ and Dart, and manually changed all the direct and indirect references to the ID across the entire codebase.

This effort took around two years to complete, and the changes have been carefully rolled out to production to avoid unexpected changes in any of the immediate and downstream systems.

Conducting this migration manually has been tedious, time consuming and stressful for the developers due to various factors.

**Finding references accurately**: Using regex is a fairly simple technique to find references across the codebase. However, it suffers from several accuracy problems.

First, regex can match named variables, parameters and references throughout the code. However, it will likely find extra references that do not need changing, or will miss references that potentially need to be updated. As an example, line 13 in Listing 2 can be matched by a regex as ".\*getToyId.\*". When toy\_id is updated to int64, the existing code still compiles since firstBitIsOne on line 17 accepts a long value, creating unnecessary work for developers to manually investigate it. Furthermore, regex will not match the value 31 on the same line, even though it needs to be updated to 63.

Additionally, some ID names are quite short, and can match other unrelated IDs across the codebase. As an example, when migrating toy\_id, regular expressions might also match another irrelevant ID field named toy\_id\_processed. This makes manual investigation of referencing code even more tedious for developers.

Changing code manually: Assuming developers carefully investigate and find all the code locations that need to be updated, they still need to check call sites and indirect references, and change all code manually, an error prone, tedious process. As an example, in Listing 2, line 13 needs to be updated to use 63 instead of 31. Developers can miss such changes, especially when the number of locations to be updated is large.

Changing tests manually: In addition to production code, there is typically accompanying test code that needs to be updated to catch potential problems in production code early. In Listing 2, the ID of the test toy on lines 27 and 39 would benefit from updating to larger values. Such test code can easily be missed by developers if updated manually.

Verifying changes manually: At Google, when developers make a code change, they typically run the regression test suite to verify that their changes did not inadvertently alter existing functionality. When regression tests fail, developers manually investigate the root cause of the failure. There are typically hundreds to thousands of changes across the codebase when migrating an ID, verifying these changes and investigating regression test failures at such scale seriously hinders developer productivity.

## 3 Automated Migration

Due to the difficulties in performing manual migrations discussed in the previous section, we built a system that leverages several components to perform ID migrations mostly automatically end to end, summarized in the high level overview in Figure 1. We previously shared high-level information about this work [46, 47], in this paper we discuss our approach, success metrics, results and learnings in great detail.

This system runs nightly until all locations are processed and there are no outstanding locations left to be migrated. A migration does not follow a waterfall model to be fully completed. Instead it is typically a continuous process where code locations are migrated over time over many sessions potentially by several developers until there are no more locations to migrate.

We discuss each component of the system in the sections below.

#### 3.1 Find Potential References

The initial input for a migration is an ID field, similar to toy\_id discussed in Listing 1. Google uses a monolithic code repository [42, 54], and a code indexing system called Kythe [25] that indexes the entire codebase in the repository. Using Kythe, we first find the direct references to the ID, then find the direct references to those references, and keep finding other indirect references to the ID in the entire codebase for a maximum total distance of five. There are some important implications of this approach.

**Irrelevance**: Our approach finds direct and indirect ID references, some of which actually do not need to be changed. As an example, in Listing 2, our approach finds lines 5, 13, 27, 39 as direct references, lines 2, 12, 25, 35, 37 as distance two indirect references since they contain the direct references, and lines 1, 22, 36, 42 as distance three indirect references as they either contain or call the distance two references.

This list contains code locations that do not necessarily need to be modified during the migration, i.e. we opt to be conservative to avoid missing any references and use a super-set of the locations that require changing.

We tackle this challenge using several techniques, e.g. classifying locations with automation, and using an LLM to output its decision on identified locations, discussed in Section 3.2.

**Incompleteness**: After a certain distance, the list of references grows quite large with little upside regarding the relevance of the found locations. Therefore, due to practical reasons, our approach considers ID references up to a distance of five, beyond which it can potentially miss some references.

We tackle this challenge by running regression test suites of the code owning teams, discussed in Section 3.3, and in some cases, by rolling out changes in production slowly to observe any potential adverse effects, discussed in Section 4.3.

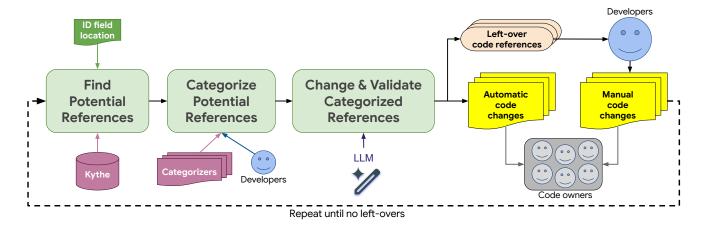


Figure 1: High level overview of the automated ID migration system. The system runs nightly, finds potential ID references and categorizes them. Developers make the necessary code changes using an LLM or manually (if the LLM failed to make the change), and send the changes to code owners. This process continues until no more ID references are left over to migrate.

**Precision**: Direct references to an ID do not always constitute the exact locations in code to be modified. In Listing 2, line 39 is identified as a direct reference to toy\_id, although the actual changes need to be performed on lines 36 and 37, as they contribute to the reference on line 39 through data flow. Our approach is not precise in exactly identifying lines 36 and 37, but precise enough to identify line 39, close to the actual needed change locations.

We tackle this challenge by relying on an LLM to consider the files to be modified in their entirety and to make changes anywhere in the passed file, even though we are not precise on the exact lines to be changed in our prompt to the LLM, discussed in Section 3.3.

It is possible to overcome these accuracy problems in the identified potential references using approaches such as data flow analysis [33] and using an AST [43] parser. However, these techniques are potentially computationally expensive, and require implementing and maintaining logic to predict and cover many potential code variations written in different styles by thousands of developers over many years, a costly, imprecise and practically intractable approach. As a result, we opted to take an inaccurate yet practical approach to finding potential references to the ID, and using an LLM to bridge the gaps in accuracy, discussed in the later sections.

#### 3.2 Categorize Potential References

After finding the potential references, we categorize them into buckets based on confidence on whether they need to be migrated or not. The categories are listed below with example categorizers used to categorize each location.

Not-migrated: This is a location that is identified to have not been migrated with 100% confidence. A typical categorizer that identifies a test location as not-migrated uses a regex to match the value used in accessor methods. As an example, in Listing 2 line 27, a regex checks the value -5, identifies it as a value inside the int32 range in Java, and marks it as not-migrated. There are more categorizers for both production and test code, and for different programming

languages.

Irrelevant: This is a location that is determined to be irrelevant with 100% confidence. As an example, a regex categorizer would mark line 27 in Listing 2 as irrelevant, if the value were to be outside the int32 range in Java. Another categorizer categorizes lines 1, 2, 12, 22, 25, 35 as irrelevant, as these are either class or method definitions, and are not relevant to the migration. Finally, developers investigate "left-over" locations discussed below, and may decide that specific locations do not require migration by marking them as irrelevant explicitly in the configuration of the system.

Relevant: This is a location that is not marked as "not-migrated" or "irrelevant", yet it is a reference to the ID field, and needs to be investigated. In Listing 2, lines 13 and 39 are marked as relevant, since they cannot be marked as not-migrated or irrelevant by earlier categorizers, yet they access toy\_id, and should potentially be investigated further.

**Left-over**: This is a location that is not categorized into any of the previous categories and is left over to be investigated by developers manually. In their investigation, developers may decide whether a location needs to be migrated or is irrelevant, which they dictate through configuration. In the next run of the system, the investigated location is moved into the dictated category, not-migrated or irrelevant.

## 3.3 Change & Validate Categorized References

To make the code changes, we leverage an internal version of the Gemini [64] model fine-tuned on internal Google code and data [42, 54] using the DIDACT framework [41] with multiple tasks for software engineering, including code-review comment resolution, edit prediction, variable renaming, code-review comment prediction, and build-error repair [23]. Although the LLM model has continuously been updated, we used the same fixed version of it with temperature=0.0 throughout the course of our study for

```
toy_id should be of type long. Update the code and respective references properly.

Also update the tests to reflect a large id. Initialize the toy_ids with values larger than 10000000000, e.g. if the previous id was 1, it should now be 10000000001L. If the previous id was negative, the new value should also be negative.
```

Listing 4: Prompt to update toy\_id references in production and test code in Java.

```
final class ToyView {
public static HtmlView showToy(Toy toy) {
  if (toyIsProducedAfter2024(toy)) {
    // Create panel with "new" badge
    final int toyId = toy.getToyId();
  final long toyId = toy.getToyId();
```

Figure 2: Example edit on a file in a code change and its diff in the UI of Critique [58], the web-based code review system used at Google. Deleted code is in red, added code is in green, Levenshtein [38] edit distance  $(\Delta)$  is 4.

stability, we did not fine-tune the model for our specific task, and only used prompting for the code modifications.

After categorizing potential references into buckets, we use the LLM to make code changes on the locations categorized as Notmigrated and Relevant, by using language-appropriate prompts, shown in Listing 4 for Java, and passing the entire file to be modified with the suggested lines of the respective locations to the LLM.

The full contents of the file ToyView. java in Listing 2 and line numbers 5, 13 is passed to the LLM for modifications. Similarly, the full contents of the file ToyViewTest. java and line numbers 27, 36, 37, 39, 42 are passed to the LLM constructing the model prompt. The passed line numbers are suggestive, and the LLM has flexibility on making changes in other lines anywhere in the file. The line suggestions are represented in the model prompt as comments instructing the model of what should be changed in the given line.

The LLM outputs changes in the form of *diffs* [27, 71], which are applied to the original file using a fuzzy diffing algorithm. This finds the locations of code to replace by using edit distance to minimize simple LLM errors. An example diff is shown in Figure 2 in the UI of Critique [58], the web-based code review system used at Google, where deleted code is in red, and added code is in green.

Since LLMs are non-deterministic, three rounds of modifications are attempted for each file, and a random change from among the successful attempts is chosen for each file.

As LLMs may produce erroneous code [16, 69], the LLM's response and its changes on an entire file are validated using several strategies in the following order:

(1) **Success**: If the LLM did not return a successful completion, the change is invalid. There are several reasons that may cause an unsuccessful completion response: the LLM server may be down, the calling system's LLM resource quota

- may be exhausted, the size of the input file may exceed the LLM's allowed context length limit.
- (2) Whitespace: If the LLM only changed whitespaces, i.e. it simply reformatted the code, the change is invalid.
- (3) AST parser: If the changed file cannot be parsed with an AST parser, i.e. it is malformed, or the AST of the changed file is identical with the original, the change is invalid.
- (4) **Punt**: We pass the files' contents before and after the change, and ask the LLM whether the change was necessary. If the LLM punts by responding "No", the change is invalid.
- (5) Build: If the changed file causes build breakages during compilation, the change is invalid.
- (6) Test: If the changed file causes regression test failures, the change is invalid.

The validations are conducted in the listed order from less expensive to more expensive. If the changed file fails any of the validations, it is discarded without running further validations, and marked to be migrated manually by developers. If the file is successfully modified by the LLM and passes all validation steps, it is marked to be ready for review.

In the end, all changed files, automatically modified by the LLM or manually modified by developers, are grouped into code changes with potentially several changed files per change, each change is visually investigated by developers for verification, any necessary final changes are manually performed within the code change by developers, and finally each code change is sent to the owners of the code for final acceptance and submission through Critique [58], shown in Figure 2.

## 4 Evaluation and Discussion

In this section, we discuss how we evaluate our system, describe our case studies, and report the results of our interviews on the usability of our system.

#### 4.1 Evaluation Metrics: LLM∆ and Human∆

To evaluate the effectiveness of the automation of our system, we use the number of characters edited by humans and LLMs to complete an ID migration. The output of our system is a code change, with one or more changed files in it. A code change falls into one of three categories:

**LLM-Only**: The code change only contains files entirely modified by the LLM.

**LLM-then-Human**: The code change is initially generated with the files modified by the LLM, but humans changed the files further upon visual investigation of the changes.

**Human-Only**: The code change only contains files entirely modified by developers manually, with no involvement from the LLM.

Examples of each code change type are shown in Figure 3, where *code-change-1* is LLM-Only, *code-change-2* is LLM-then-Human, and *code-change-3* is Human-Only.

In all code changes, *Baseline* is the version of a file that is not yet changed. Once a file is modified and saved, a *snapshot* is created.

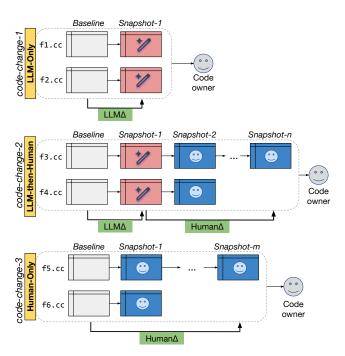


Figure 3: Types of code change, and how the number of edited characters by the LLM and developers are calculated.

Subsequent further modification and save events result in new snapshots. Between each snapshot, there are character edits to change the code to the new snapshot, shown in Figure 2, where we use Levenshtein [38] edit distance,  $\Delta$  for short, as a proxy to measure the effort required to make the modifications.

In *code-change-1*, *Snapshot-1* contains the automated LLM changes. The Levenshtein edit distance between *Baseline* and *Snapshot-1* is calculated as the LLM $\Delta$ .

In code-change-2, developers make further edits in each file in addition to the LLM changes, so the subsequent snapshots from Snapshot-2 to the final snapshot submitted with the code change contain human edits. We calculate the Levenshtein edit distance between Baseline and Snapshot-1 as the LLM $\Delta$ , and the Levenshtein edit distance between Snapshot-1 and Snapshot-n as the Human $\Delta$ . Note that, the Human $\Delta$  is not an aggregation of all the edits between each snapshot, but instead the single edit distance between Snapshot-1 and Snapshot-n, as the edits between the intermediate snapshots are considered work in progress, and are ignored for a fair comparison between LLM $\Delta$  and Human $\Delta$ .

In code-change-3, all snapshots from Snapshot-1 to Snapshot-m contain human edits, as the LLM is not involved in the edits for Human-Only code changes at all. As a result, the Levenshtein edit distance between Baseline and Snapshot-m is calculated as the Human $\Delta$ .

We track every code change in both categories, calculate the total edits across all files in all code changes related to the migration of an ID, and compare the LLM $\Delta$  and Human $\Delta$  for the entire ID.

Table 1: Aggregate statistics about the migrations.

# IDs migrated	39
# Developers that conducted migrations	3
Total code changes	595
by developer-1	290
by developer-2	251
by developer-3	54
Total code changes	595
LLM-Only	214 (35.97%)
LLM-then-Human	229 (38.48%)
Human-Only	152 (25.55%)
Total code changes	595
# reviewers	306
# teams	149
# offices	37
# time zones	12
Total∆ across all IDs	93, 574
LLMΔ	64, 996 (69.46%)
Human $\Delta$	28, 578 (30.54%)

## 4.2 Statistics On Migrated IDs

Summarized in Table 1, three developers migrated 39 distinct IDs over twelve months using our system, a total of 595 code changes have been submitted, 74.45% of the code changes (LLM-Only and LLM-then-Human) have been generated by the LLM, a total of 93,574 edits across all code changes have been performed, and 69.46% of those edits were by the LLM.

IDs have varying characteristics regarding the programming languages that reference the ID and the migration size, listed in Table 2, where IDs are sorted by descending Total $\Delta$ . While some IDs required edits spread across many files (e.g. ID-30, ID-32, ID-03), some IDs were more localized into a few files (e.g. ID-10, ID-24, ID-27).

Additionally, LLM $\Delta$  and Human $\Delta$  split is summarized as a percentage of total edits for each ID in Figure 4.

## 4.3 Discussion

At the end of the migrations, we collected the statistics discussed in the previous section and conducted interviews with the three developers that performed the migrations using our system. In this section, we summarize and discuss the developers' observations and experiences, the advantages and disadvantages they reported using the system, and highlight important differences in the characteristics of the migrated IDs.

Automation benefits: The developers reported great satisfaction with the end-to-end automation of the code changes, especially when the LLM worked well and suggested the correct modifications. Our system ran nightly, and promoted the code changes that passed all validations to be reviewed by developers. Then, the developers investigated the code changes for final verification and sent them out to code owners. 74.45% of the code changes have been automatically created by the system, resulting in high productivity.

Table 2: Statistics for each migrated ID.

	Total∆↓	# Code	# Modified	# Duo muo manin m
	ιοιαιΔ↓		# Modified Files	# Programming
ID 20	93900	Changes 39		Languages
ID-30	23800		418	2
ID-32	22822	185	392	5
ID-20	16406	28	175	2
ID-28	7059	29	89	1
ID-03	4594	21	350	4
ID-37	2774	25	58	1
ID-06	2458	23	41	2
ID-35	2039	14	38	2
ID-19	1937	17	21	1
ID-18	1889	20	33	1
ID-29	1825	6	38	1
ID-04	1279	10	27	1
ID-31	1223	15	31	1
ID-26	1151	4	11	1
ID-34	1088	4	16	2
ID-09	1038	6	16	1
ID-38	844	8	17	2
ID-14	802	7	12	2
ID-01	798	16	103	4
ID-07	673	7	31	1
ID-05	584	5	9	1
ID-08	578	6	13	2
ID-22	571	2	19	1
ID-17	538	4	6	1
ID-36	386	5	8	2
ID-12	374	5	40	4
ID-02	367	10	14	1
ID-23	326	10	15	1
ID-33	299	7	7	2
ID-13	270	8	14	2
ID-27	221	5	6	1
ID-15	221	11	12	2
ID-16	156	9	13	2
ID-21	146	3	10	1
ID-25	128	7	11	1
ID-10	98	1	4	1
ID-11	95	7	7	2
ID-24	26	2	2	1
ID-39	23	1	1	1

For changes that they had to manually create, the developers still reported high satisfaction with the accuracy of the potential references found for them to investigate, compared to their previous regex based approach. They estimated that, compared to their previous attempts, this system reduced the total time spent on a migration by 50%. We do not have concrete wall-clock effort measurements on the total time spent, although the percentage of automatically created code changes, 74.45%, and the total LLM $\Delta$  across all migrations, 69.46%, directionally align with the developers' estimate.

Additionally, as our system runs nightly and updates the remaining left-over references automatically using the submitted code

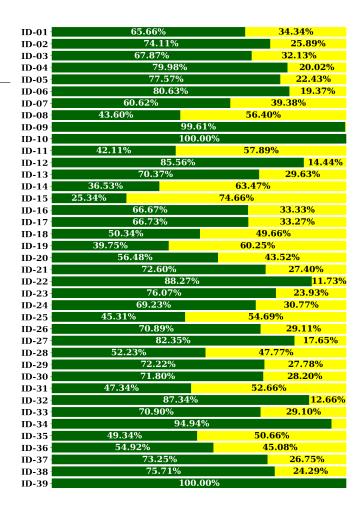


Figure 4: LLM $\triangle$  and Human $\triangle$  percentages for each ID.

changes, the developers reported to have a continuously renewed state of the migration, providing a sense of progress towards the completion of the migration.

Validation benefits: The developers highlighted automated validations as a significant improvement on their productivity. Before automation, in addition to their manual edits, developers needed to create the code change, start validations manually, and wait for them to finish before they decide whether the code change is ready for review by code owners. Our system only promotes those code changes that pass all validation steps that are ready for review, decreasing the tedious work developers need to undertake.

**LLM benefits**: The developers reported high satisfaction with the use of an LLM to suggest modifications. There are a myriad different ways developers write code, and it is practically prohibitive to predict all potential uses and expensive to declare and maintain code transformations with popular rule based tools such as TXL [14], Stratego/XT [11], Rascal [34].

LLMs are reported to have good representation and reasoning on code [3, 22, 39, 45], making it possible to ask for intended changes

```
public static final int MAX_TOY_ID = 69234567;
public static final long MAX_TOY_ID = 1000069234567L;
inline constexpr int kMaxToyId = 69234567;
4 inline constexpr int64_t kMaxToyId = 1000069234567;
```

(a) Changes in multiple languages with almost identical prompt

```
int nonExistingToyId = RANDOM.nextInt();
8 long nonExistingToyId = RANDOM.nextLong();
```

(b) Language specific domain knowledge

```
7 public void test_queryToys() {
    Toy toy = Toy.newBuilder().setToyId(1).build();
8 Toy toy = Toy.newBuilder().setToyId(1000000000000).build();
9 Truth.assertThat(ToyStore.getToyQuery(toy))
10 .isEqualTo( //
    "SELECT * FROM Toys WHERE ToyId = 1");
11 "SELECT * FROM Toys WHERE ToyId = 100000000000");
```

(c) Updating values in code and in SQL strings together

```
public void testToyIdStorage() {

final int initialToyId = 1;
final long initialToyId = 1000000000000L;

storeToyWithId(initialToyId++, 23);
storeToyWithId(initialToyId++, 34);
storeToyWithId(initialToyId++, 12);
```

(d) Making the minimal change instead of changing all lines

Figure 5: Examples of LLM edits.

using a standard prompt in English to tackle a wide variety of code patterns. Several examples where production code is adapted to our working example to mirror actual submitted code changes, are shown in Figure 5, demonstrating the LLM's domain knowledge, flexibility, and its ability to change relevant code.

Figure 5a shows an example test where an almost identical prompt results in the successful update of Java and C++ code. In Figure 5b, the LLM exhibits domain knowledge on the appropriate method to call in Java after the migration. Figure 5c shows an example where the LLM correctly identifies and changes not only code but also its counterpart in the SQL string. Finally, in Figure 5d, even though the LLM is passed three distinct line numbers to change in the file, lines 9, 10 and 11, and even though those lines contain multiple numbers that could potentially be confusing, the LLM identifies the right number to change, i.e. initialToyId, and makes the minimal change of updating line 7, instead of the three lines suggested.

Developers reported satisfaction on the LLM's ability to flexibly cover such different cases in different programming languages, removing the burden of implementing and maintaining code transformation rules or tooling.

**LLM non-determinism challenges**: LLMs exhibit non-deterministic behavior, resulting in varied output diffs even when presented with identical inputs across multiple executions. This inherent variability elicited mixed reactions from developers, expressing satisfaction

```
Toy toy = Toy.newBuilder().setToyId(toyId).build();
Toy toy = Toy.newBuilder()

setToyId(toyId)

build();
```

(a) Hallucination that reformats file contents

```
Toy toy = Toy.newBuilder().setToyId(1369873).build();
Toy toy = Toy.newBuilder().setToyId(/* toyId */ 1369873).build();
```

(b) Hallucination that adds comments

Figure 6: Examples of LLM hallucinations.

and dissatisfaction under different use-cases. When the LLM does not work on a file, developers reported satisfaction on the ability to re-run it on the same inputs several times and to sometimes get a satisfactory code change in the end. This unpredictability also led to dissatisfaction when the LLM failed, as developers could not anticipate how many retries would be needed before resorting to manual changes, and they were unhappy about any manual work they had to carry out in the end.

**LLM context-window challenges**: One of the limitations of using an LLM is the input context window size, some edits were not performed by the LLM as the entire contents of a large file did not fit into the context window<sup>1</sup>. Such change attempts failed in the first validation step "Success" in Section 3.3, and those changes had to be performed by the developers manually.

**LLM hallucination challenges**: The LLM sometimes had hallucinations, where it simply reformatted the code as in Figure 6a, only added comments to the code as in Figure 6b, or made entirely irrelevant changes. Developers had to manually handle such cases, constituting 25.55% of the code changes and 30.54% of the edits.

**LLM language support challenges**: Certain languages, including Java, C++, and Python were well supported by the used LLM, while Dart was not well supported, as the LLM was not trained on enough Dart code. As a result, IDs with heavy Dart use, e.g. ID-15, ID-31 and ID-35, ended up with lower LLMΔ percentages.

Ramp-up: When the developers first started the migrations, they were not familiar with using our system. To maximize the benefits of automation provided by the system, they started with smaller, localized IDs. Until they familiarized themselves to use the system effectively, they ended up making some of the edits manually. As they gained more experience, they moved on to larger, more spread IDs, with higher use of automation. This directly contributed to the differences between the LLM $\Delta$  and Human $\Delta$  split observed across different IDs shown in Figure 4. For instance, ID-24 and ID-25 have low Total  $\Delta$ , but also low LLM $\Delta$  percentages, while ID-30 has the highest Total  $\Delta$ , yet it has a high LLM $\Delta$  of 71.80%.

**Pre-existing failures**: At Google, each code change goes through regression testing before submission. If the regression test suite has pre-existing failures unrelated to the code change under review,

<sup>&</sup>lt;sup>1</sup>This is mitigated in the latest Gemini versions with a much larger context window

validation of the code change fails at the "Test" step discussed in Section 3.3. This has been a hindrance for the developers during migrations, even though the LLM has been successful in some of the code changes, those code changes were not promoted for review, and developers had to contact the code owners to fix the pre-existing failures and only after then made the code changes related to the ID migration.

**Pre-existing goldens**: At Google, expected outputs of tests, called *goldens*, are sometimes stored in the source code repository along with characterization tests [19]. When test code is updated, goldens typically require manual updates from developers by running specialized tools. As our automated system did not support running such tools, tests using goldens sometimes failed the "Test" step discussed in Section 3.3, and required manual work from developers, contributing to lower LLMΔ percentages.

**Production roll-outs**: Small, localized ID migrations were typically completed by the developers entirely without a need for additional work. However, large, distributed IDs, a total of 2 out of the 39 migrated, namely ID-30 and ID-32, required attention from the code owners before they were rolled out into production. As the impact of such IDs potentially spanned across several teams, changes were rolled out slowly to observe any adverse effects. Our system provided no automation or benefits for this step.

The findings of this study, encompassing both the advantages and disadvantages of our system, alongside developer feedback, indicate that our approach strikes an effective balance between automation and user oversight for the specific migration task within Google's infrastructure. We posit that the high-level workflow implemented in our system, especially using an LLM but verifying its proposed changes through tooling, could be adapted for various types of migrations in different development environments, thereby providing a foundation for LLM-assisted automation to support developers.

## 5 Threats To Validity

In this section, we discuss the threats to the validity of our work and case studies.

**Case study**: Our case study does not involve a controlled experiment comparing the LLM-based approach to other techniques, making it difficult to isolate the specific contribution of the different components of the system to the observed improvements.

Additionally, our case study was conducted within the specific context of Google's development environment and infrastructure, which may limit the generalizability of the findings to other organizations

Our case study involved 39 ID migrations conducted by three developers, which may not be representative of the full range of other types of code migration tasks and developer experiences.

Finally, our case study focuses on a specific type of code migration, migrating identifiers from 32-bits to 64-bits. Our results may not generalize to other types of migrations.

**Developer Bias**: The developers involved in the case study were also involved in the development of the system by providing feedback, potentially introducing bias in their assessment of the system's effectiveness.

**LLM**: Our study uses an LLM developed to be used internally at Google. Although popular large LLMs have been shown to perform well on tasks such as summarization and question answering, the generalizability of our results on migrations to other LLMs may be limited.

**Effort estimation**: The study uses Levenshtein edit distance as a measure of developer effort, which may not fully capture the cognitive load and complexity involved in code modifications.

Furthermore, the reported 50% time savings is based on developer perception and estimations, and not on precise time tracking data. Although their estimations are in line with the proportion of automatically generated code changes and edits, there may be potential inaccuracies in their assessment of efficiency gains.

#### 6 Related Work

There has been extensive research in literature on manipulating code under different domains including code migration, code transformation, and code refactoring, all relevant to our work. Code translation is, to a degree, another relevant domain to the work discussed in this paper.

**Code translation**: Early research on code translation relied on manually defined rules and various program analysis techniques that operate on different abstractions on the source code.

There has been work on using parse trees [13] and abstract syntax trees [43] generated from source code, transformed and fed to the target compiler [1, 2, 20, 70]. Yasumatsu and Doi [74] built a system that creates runtime replacement classes between Smalltalk and C to implement the same functionality. Baker [8] uses parameterized pattern matching techniques on a stream-of-strings representation of source code to map patterns to the destination language. SCRUPLE [52] uses regular-expressions to locate and translate programming patterns between languages. Johnson [30] uses hash-based fingerprints to identify text-level patterns in source code to be translated to the target language. Syntax based editing approaches have also been used for code translation [9, 10, 12, 37, 56, 63]. These approaches require either manually creating rules for translation or implementing specific tooling, a time consuming task with potentially unintended results including low readability and low accuracy of the translated code [35].

More recently, effectiveness of LLMs for code translation tasks has been investigated extensively. Weixiang et al. [72] propose a benchmark to assess the success of code translation tasks. SteloCoder [50] uses LLMs to translate code into Python, while FLOURINE [18] translates source code to Rust. TRANSAGENT [75] and TransCoder [57] translate code between several programming languages using automated validation and fixing mechanisms to improve accuracy. UniTrans [73] uses test-cases as a benchmark and to guide code translation between multiple programming languages. CoTran [29] augments LLMs to translate code by using symbolic execution based

testing and reinforcement learning on the LLM outputs. A recent study by Pan et al. [51] points out the shortcomings of LLM-based code translation approaches by demonstrating various mistakes LLMs make.

Our work is different from code translation, as we modify code within the same language to obtain minor differences in its behavior.

**Code transformation**: Early research on code transformation has been rule-based where transformations are specified using manually defined rules, such as TXL [14], Stratego/XT [11], Rascal [34].

Gabel and Su [24] showed high redundancy and repetitiveness within short windows of source code when analyzed with syntactical tokens. This led to further studies [44] that exploit the repetitiveness to suggest transformation by example [40], where an example transformation is used to form an abstraction to be applied to similar code.

LLMs have also been used for transformation by example recently. PyCraft [15] uses a combination of static analysis, dynamic analysis, and LLMs with few shot learning to generate variants of input examples for conditional programmed attribute grammars. InferRules [32] infers transformation rules from code examples in Java and Python.

CodePlan [7] uses LLMs for code transformation, specifically focusing on repository-level changes using AI planning techniques and incremental dependency analysis to iteratively change code until it satisfies desired specifications. MELT [55] utilizes GPT-4 to automatically generate transformation rules for Python libraries from code examples found in pull requests.

Another popular application of LLMs is for automating extract method refactoring [21] which involves taking a section of code from a method and placing it in a new method. LM-Assist [53] combines LLMs with static analysis techniques and uses the IDE to perform refactoring. Revamp [49] focuses on refactoring abstract data types using relational representation invariants to specify the desired changes to the data types.

Recent work explored using LLMs for automatic code migrations. Almeida et al. [4] investigates the effectiveness of using GPT 4.0 [3] to migrate eighteen methods and four tests in an application that utilized the SQLAlchemy library to a newer version. Tehrani and Anubhai [48] investigated human-AI partnerships for LLM-based code migrations by observing software developers working with Amazon Q Code Transformation to migrate systems from Java 7 to Java 18, and found that successful human-AI partnership relies on human-in-the-loop techniques.

These preliminary work are relevant to ours, though, to the best of our knowledge, our work is the largest, most comprehensive automated migration effort in scope and time frame to date.

#### 7 Conclusion and Future Work

Code migration is a critical part of software development focused on updating and improving systems to ensure ongoing functionality. Manually handling code migrations, especially for large projects, is a challenging, time-consuming, and tedious process. Much research focused on automating migrations, where LLMs are a particular area of focus recently due to their abilities to manipulate code.

In this paper, we propose an automated solution for a large-scale, costly migration project at Google that was previously conducted manually. Our solution uses change location discovery and categorization, an LLM and automated validation to perform the migration automatically.

Our case study on 39 distinct migrations over twelve months resulted in a total of 595 code changes with 93, 574 submitted edits. The LLM generated 74.45% of the submitted code changes, 69.46% of the submitted edits, and developers using our system estimated the total time spent on the migration was reduced by 50%.

Our results highlight the potential of LLMs to significantly improve developer productivity and efficiency in large-scale code migration tasks. By automating a substantial portion of the process, the system effectively minimized manual effort and saved developers considerable time. Developers highly appreciated the system's ability to accurately find potential code references, automate code changes, and validate modifications. They also noted that the continuous and automated nature of the system provided a clear sense of progress and reduced the tedious manual effort involved in code migration.

There were also challenges associated with the use of our system, namely the LLM's limited context window size and hallucinations. Additionally, the LLM's performance varied across different programming languages. Furthermore, pre-existing test failures hindered productivity and the largest migrations required safe production roll-outs.

Future research avenues include exploring ways to enhance LLM capabilities, such as increasing context window size, improving language support, mitigating hallucinations and enhancing the accuracy of code modifications, ultimately leading to improved software quality and developer productivity. Finally, a promising research direction is to use LLMs to not only assist in making code changes, but also to determine the code locations to be changed, potentially decreasing the number of left-over locations to be manually investigated.

# 8 Acknowledgments

This work is the result of a collaboration between the Google Core Developer, Google Ads and Google DeepMind teams. We thank key contributors: Priya Baliga, Siddharth Taneja, Ayoub Kachkach, Jonathan Bingham, Ballie Sandhu, Christoph Grotz, Alexander Frömmgen, Lera Kharatyan, Maxim Tabachnyk, Shardul Natu, Bar Karapetov, Kashmira Phalak, Andrew Villadsen, Maia Deutsch, AK Kulkarni, Satish Chandra, Danny Tarlow, Aditya Kini, Marc Brockschmidt, Yurun Shen, Milad Hashemi, Chris Gorgolewski, Don Schwarz, Chris Kennelly, Sarah Drasner, Niranjan Tulpule, Madhura Dudhgaonkar.

We also thank the internal Google reviewers, and the anonymous reviewers of the FSE committee.

#### References

- 2025. GitHub mono/sharpen: Sharpen is an Eclipse plugin created by db4o that allows you to convert your Java project into C#. https://github.com/mono/ sharpen [Online; Accessed January 2025].
- [2] 2025. GitHub paulirwin/JavaToCSharp. Java to C# converter. https://github.com/paulirwin/JavaToCSharp [Online; Accessed January 2025].
- [3] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal

- Anadkat, et al. 2023. Gpt-4 technical report. arXiv preprint arXiv:2303.08774 (2023).
- [4] Aylton Almeida, Laerte Xavier, and Marco Tulio Valente. 2024. Automatic Library Migration Using Large Language Models: First Results. arXiv preprint arXiv:2408.16151 (2024).
- [5] Kamel Alrashedy and Ahmed Binjahlan. 2023. Language Models are Better Bug Detector Through Code-Pair Classification. arXiv preprint arXiv:2311.07957 (2023).
- [6] Nadia Alshahwan, Jubin Chheda, Anastasia Finogenova, Beliz Gokkaya, Mark Harman, Inna Harper, Alexandru Marginean, Shubho Sengupta, and Eddy Wang. 2024. Automated unit test improvement using large language models at meta. In Companion Proceedings of the 32nd ACM International Conference on the Foundations of Software Engineering. 185–196.
- [7] Ramakrishna Bairi, Atharv Sonwane, Aditya Kanade, Arun Iyer, Suresh Parthasarathy, Sriram Rajamani, B Ashok, and Shashank Shet. 2024. Codeplan: Repository-level coding using llms and planning. Proceedings of the ACM on Software Engineering 1, FSE (2024), 675–698.
- [8] Brenda S Baker. 1996. Parameterized pattern matching: Algorithms and applications. Journal of computer and system sciences 52, 1 (1996), 28–42.
- [9] Robert A Ballance, Susan L Graham, and Michael L Van De Vanter. 1992. The Pan language-based editing system. ACM Transactions on Software Engineering and Methodology (TOSEM) 1, 1 (1992), 95–127.
- [10] Patrick Borras, Dominique Clément, Th Despeyroux, Janet Incerpi, Gilles Kahn, Bernard Lang, and Valérie Pascual. 1988. Centaur: the system. ACM Sigplan Notices 24, 2 (1988), 14–24.
- [11] Martin Bravenboer, Karl Trygve Kalleberg, Rob Vermaas, and Eelco Visser. 2008. Stratego/XT 0.17. A language and toolset for program transformation. Science of computer programming 72, 1-2 (2008), 52-70.
- [12] Y-F Chen, Michael Y. Nishimoto, and CV Ramamoorthy. 1990. The C information abstraction system. IEEE Transactions on software Engineering 16, 3 (1990), 325– 334.
- [13] Ian Chiswell and Wilfrid Hodges. 2007. Mathematical logic. OUP Oxford.
- [14] James R Cordy. 2004. TXL-a language for programming language tools and applications. Electronic notes in theoretical computer science 110 (2004), 3-31.
- [15] Malinda Dilhara, Abhiram Bellur, Timofey Bryksin, and Danny Dig. 2024. Unprecedented code change automation: The fusion of llms and transformation by example. Proceedings of the ACM on Software Engineering 1, FSE (2024), 631–653.
- [16] Shihan Dou, Haoxiang Jia, Shenxi Wu, Huiyuan Zheng, Weikang Zhou, Muling Wu, Mingxu Chai, Jessica Fan, Caishuang Huang, Yunbo Tao, et al. 2024. What's Wrong with Your Code Generated by Large Language Models? An Extensive Study. arXiv preprint arXiv:2407.06153 (2024).
- [17] Shubhang Shekhar Dvivedi, Vyshnav Vijay, Sai Leela Rahul Pujari, Shoumik Lodh, and Dhruv Kumar. 2024. A comparative analysis of large language models for code documentation generation. In Proceedings of the 1st ACM International Conference on AI-Powered Software. 65–73.
- [18] Hasan Ferit Eniser, Hanliang Zhang, Cristina David, Meng Wang, Maria Christakis, Brandon Paulsen, Joey Dodds, and Daniel Kroening. 2024. Towards translating real-world code with llms: A study of translating to rust. arXiv preprint arXiv:2405.11514 (2024).
- [19] Michael Feathers. 2004. Working effectively with legacy code. Prentice Hall Professional.
- [20] Stuart I Feldman. 1990. A Fortran to C converter. In ACM SIGPLAN Fortran Forum, Vol. 9. ACM New York, NY, USA, 21–22.
- [21] Martin Fowler. 2018. Refactoring: improving the design of existing code. Addison-Weslev Professional.
- [22] Daniel Fried, Armen Aghajanyan, Jessy Lin, Sida Wang, Eric Wallace, Freda Shi, Ruiqi Zhong, Wen-tau Yih, Luke Zettlemoyer, and Mike Lewis. 2022. Incoder: A generative model for code infilling and synthesis. arXiv preprint arXiv:2204.05999 (2022).
- [23] Alexander Frömmgen, Jacob Austin, Peter Choy, Nimesh Ghelani, Lera Kharatyan, Gabriela Surita, Elena Khrapko, Pascal Lamblin, Pierre-Antoine Manzagol, Marcus Revaj, et al. 2024. Resolving Code Review Comments with Machine Learning. In Proceedings of the 46th International Conference on Software Engineering: Software Engineering in Practice. 204–215.
- [24] Mark Gabel and Zhendong Su. 2010. A study of the uniqueness of source code. In Proceedings of the eighteenth ACM SIGSOFT international symposium on Foundations of software engineering. 147–156.
- [25] Google. 2012. Kythe. https://kythe.io [Online; Accessed January 2025].
- [26] André Hora, Romain Robbes, Nicolas Anquetil, Anne Etien, Stéphane Ducasse, and Marco Tulio Valente. 2015. How do developers react to api evolution? the pharo ecosystem case. In 2015 IEEE International Conference on Software Maintenance and Evolution (ICSME). IEEE, 251–260.
- [27] James Wayne Hunt and M Douglas Macllroy. 1976. An algorithm for differential file comparison. Bell Laboratories Murray Hill.
- [28] Saki Imai. 2022. Is github copilot a substitute for human pair-programming? an empirical study. In Proceedings of the ACM/IEEE 44th International Conference on Software Engineering: Companion Proceedings. 319–321.

- [29] Prithwish Jana, Piyush Jha, Haoyang Ju, Gautham Kishore, Aryan Mahajan, and Vijay Ganesh. 2023. CoTran: An LLM-based Code Translator using Reinforcement Learning with Feedback from Compiler and Symbolic Execution. arXiv preprint arXiv:2306.06755 (2023).
- [30] J Howard Johnson. 1994. Substring Matching for Clone Detection and Change Tracking.. In ICSM, Vol. 94. 120–126.
- [31] Sungmin Kang, Gabin An, and Shin Yoo. 2024. A quantitative and qualitative evaluation of LLM-based explainable fault localization. Proceedings of the ACM on Software Engineering 1, FSE (2024), 1424–1446.
- [32] Ameya Ketkar, Oleg Smirnov, Nikolaos Tsantalis, Danny Dig, and Timofey Bryksin. 2022. Inferring and applying type changes. In Proceedings of the 44th International Conference on Software Engineering. 1206–1218.
- [33] Gary A Kildall. 1973. A unified approach to global program optimization. In Proceedings of the 1st annual ACM SIGACT-SIGPLAN symposium on Principles of programming languages. 194–206.
- [34] Paul Klint, Tijs Van Der Storm, and Jurgen Vinju. 2009. Rascal: A domain specific language for source code analysis and manipulation. In 2009 Ninth IEEE International Working Conference on Source Code Analysis and Manipulation. IEEE, 168–177.
- [35] Kostas Kontogiannis, Johannes Martin, Kenny Wong, Richard Gregory, Hausi Müller, and John Mylopoulos. 2010. Code migration through transformations: An experience report. In CASCON First Decade High Impact Papers. 201–213.
- [36] Raula Gaikovina Kula, Daniel M German, Ali Ouni, Takashi Ishio, and Katsuro Inoue. 2018. Do developers update their library dependencies? An empirical study on the impact of security advisories on library migration. *Empirical Software Engineering* 23 (2018), 384–417.
- [37] David A Ladd and J Christopher Ramming. 1995. A\*: A language for implementing language processors. IEEE Transactions on Software Engineering 21, 11 (1995), 894–901.
- [38] V Levenshtein. 1966. Binary codes capable of correcting deletions, insertions, and reversals. Proceedings of the Soviet physics doklady (1966).
- [39] Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, Jia Li, Jenny Chim, et al. 2023. Starcoder: may the source be with you! arXiv preprint arXiv:2305.06161 (2023).
- [40] Henry Lieberman. 2001. Your wish is my command: Programming by example. Morgan Kaufmann.
- [41] Petros Maniatis and Daniel Tarlow. 2023. Large sequence models for software development activities. https://research.google/blog/large-sequence-models-forsoftware-development-activities [Online; Accessed January 2025].
- [42] Atif Memon, Zebao Gao, Bao Nguyen, Sanjeev Dhanda, Eric Nickell, Rob Siemborski, and John Micco. 2017. Taming Google-Scale Continuous Testing. In Proceedings of the 39th International Conference on Software Engineering: Software Engineering in Practice Track. IEEE Press, 233–242.
- [43] Philip H. Newcomb and Ravindra Naik. 2011. Architecture-driven Modernization: Abstract Syntax Tree Metamodel (ASTM). https://www.omg.org/spec/ASTM/1. 0/PDF. [Online; Accessed January 2025].
- [44] Hoan Anh Nguyen, Anh Tuan Nguyen, Tung Thanh Nguyen, Tien N Nguyen, and Hridesh Rajan. 2013. A study of repetitiveness of code changes in software evolution. In 2013 28th IEEE/ACM International Conference on Automated Software Engineering (ASE). IEEE, 180–190.
- [45] Erik Nijkamp, Bo Pang, Hiroaki Hayashi, Lifu Tu, Huan Wang, Yingbo Zhou, Silvio Savarese, and Caiming Xiong. 2022. Codegen: An open large language model for code with multi-turn program synthesis. arXiv preprint arXiv:2203.13474 (2022).
- [46] Stoyan Nikolov, Daniele Codecasa, Anna Sjovall, Maxim Tabachnyk, Satish Chandra, Siddharth Taneja, and Celal Ziftci. 2025. How is Google using AI for internal code migrations?. In Proceedings of the 47th International Conference on Software Engineering: Software Engineering in Practice Track. In press.
- [47] Stoyan Nikolov and Siddharth Taneja. 2024. Accelerating code migrations with AI. https://research.google/blog/accelerating-code-migrations-with-ai [Online; Accessed January 2025].
- [48] Behrooz Omidvar Tehrani and Anmol Anubhai. 2024. Evaluating Human-AI Partnership for LLM-based Code Migration. In Extended Abstracts of the CHI Conference on Human Factors in Computing Systems. 1–8.
- [49] Shankara Pailoor, Yuepeng Wang, and Işıl Dillig. 2024. Semantic code refactoring for abstract data types. Proceedings of the ACM on Programming Languages 8, POPL (2024), 816–847.
- [50] Jialing Pan, Adrien Sadé, Jin Kim, Eric Soriano, Guillem Sole, and Sylvain Flamant. 2023. SteloCoder: a Decoder-Only LLM for Multi-Language to Python Code Translation. arXiv preprint arXiv:2310.15539 (2023).
- [51] Rangeet Pan, Ali Reza Ibrahimzada, Rahul Krishna, Divya Sankar, Lambert Pouguem Wassi, Michele Merler, Boris Sobolev, Raju Pavuluri, Saurabh Sinha, and Reyhaneh Jabbarvand. 2024. Lost in translation: A study of bugs introduced by large language models while translating code. In Proceedings of the IEEE/ACM 46th International Conference on Software Engineering. 1–13.
- [52] Santanu Paul and Atul Prakash. 1994. A framework for source code search using program patterns. IEEE Transactions on Software Engineering 20, 6 (1994), 463–475.

- [53] Dorin Pomian, Abhiram Bellur, Malinda Dilhara, Zarina Kurbatova, Egor Bogomolov, Timofey Bryksin, and Danny Dig. 2024. Together We Go Further: LLMs and IDE Static Analysis for Extract Method Refactoring. arXiv preprint arXiv:2401.15298 (2024).
- [54] Rachel Potvin and Josh Levenberg. 2016. Why Google stores billions of lines of code in a single repository. Commun. ACM 59, 7 (2016), 78–87.
- [55] Daniel Ramos, Hailie Mitchell, Inês Lynce, Vasco Manquinho, Ruben Martins, and Claire Le Goues. 2023. MELT: Mining Effective Lightweight Transformations from Pull Requests. In 2023 38th IEEE/ACM International Conference on Automated Software Engineering (ASE). IEEE, 1516–1528.
- [56] Thomas Reps and Tim Teitelbaum. 1984. The synthesizer generator. ACM Sigplan Notices 19, 5 (1984), 42–48.
- [57] Baptiste Roziere, Marie-Anne Lachaux, Lowik Chanussot, and Guillaume Lample. 2020. Unsupervised translation of programming languages. Advances in neural information processing systems 33 (2020), 20601–20611.
- [58] Caitlin Sadowski, Emma Söderberg, Luke Church, Michal Sipko, and Alberto Bacchelli. 2018. Modern code review: a case study at Google. In Proceedings of the 40th International Conference on Software Engineering: Software Engineering in Practice. ACM, 181–190.
- [59] Max Schäfer, Sarah Nadi, Aryaz Eghbali, and Frank Tip. 2023. An empirical evaluation of using large language models for automated unit test generation. IEEE Transactions on Software Engineering (2023).
- [60] Atsushi Shirafuji, Yusuke Oda, Jun Suzuki, Makoto Morishita, and Yutaka Watanobe. 2023. Refactoring programs using large language models with fewshot examples. In 2023 30th Asia-Pacific Software Engineering Conference (APSEC). IEEE, 151–160.
- [61] Mohammed Latif Siddiq, Joanna Cecilia Da Silva Santos, Ridwanul Hasan Tanvir, Noshin Ulfat, Fahmid Al Rifat, and Vinícius Carvalho Lopes. 2024. Using large language models to generate junit tests: An empirical study. In Proceedings of the 28th International Conference on Evaluation and Assessment in Software Engineering. 313–322.
- [62] Dominik Sobania, Martin Briesch, Carol Hanna, and Justyna Petke. 2023. An analysis of the automatic bug fixing performance of chatgpt. In 2023 IEEE/ACM International Workshop on Automated Program Repair (APR). IEEE, 23–30.
- [63] Joseph L Steffen et al. 1985. Interactive examination of a C program with Cscope. In Proceedings of the USENIX Winter Conference. 170–175.
- [64] Gemini Team, Rohan Anil, Sebastian Borgeaud, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, Katie Millican,

- et al. 2023. Gemini: a family of highly capable multimodal models. arXiv preprint arXiv:2312.11805 (2023).
- [65] Rosalia Tufano, Simone Masiero, Antonio Mastropaolo, Luca Pascarella, Denys Poshyvanyk, and Gabriele Bavota. 2022. Using pre-trained models to boost code review automation. In Proceedings of the 44th international conference on software engineering. 2291–2302.
- [66] Rosalia Tufano, Luca Pascarella, Michele Tufano, Denys Poshyvanyk, and Gabriele Bavota. 2021. Towards automating code review activities. In 2021 IEEE/ACM 43rd International Conference on Software Engineering (ICSE). IEEE, 163–174
- [67] Kenton Varda. 2008. Google Protocol Buffers: Google's data interchange format. https://developers.google.com/protocol-buffers [Online; Accessed January 2025].
- [68] Ying Wang, Bihuan Chen, Kaifeng Huang, Bowen Shi, Congying Xu, Xin Peng, Yijian Wu, and Yang Liu. 2020. An empirical study of usages, updates and risks of third-party libraries in java projects. In 2020 IEEE International Conference on Software Maintenance and Evolution (ICSME). IEEE, 35–45.
- [69] Zhijie Wang, Zijie Zhou, Da Song, Yuheng Huang, Shengmai Chen, Lei Ma, and Tianyi Zhang. 2024. Where Do Large Language Models Fail When Generating Code? arXiv preprint arXiv:2406.08731 (2024).
- [70] Wikipedia contributors. 2024. C2Rust Demonstration. https://c2rust.com [Online; Accessed January 2025].
- [71] Wikipedia contributors. 2024. Diff Wikipedia, The Free Encyclopedia. https://en.wikipedia.org/w/index.php?title=Diff&oldid=1252179392 [Online; Accessed January 2025].
- [72] Weixiang Yan, Yuchen Tian, Yunzhe Li, Qian Chen, and Wen Wang. 2023. Codetransocean: A comprehensive multilingual benchmark for code translation. arXiv preprint arXiv:2310.04951 (2023).
- [73] Zhen Yang, Fang Liu, Zhongxing Yu, Jacky Wai Keung, Jia Li, Shuo Liu, Yifan Hong, Xiaoxue Ma, Zhi Jin, and Ge Li. 2024. Exploring and unleashing the power of large language models in automated code translation. Proceedings of the ACM on Software Engineering 1, FSE (2024), 1585–1608.
- [74] Kazuki Yasumatsu and Norihisa Doi. 1995. SPiCE: a system for translating Smalltalk programs into a C environment. IEEE Transactions on Software Engineering 21, 11 (1995), 902–912.
- [75] Zhiqiang Yuan, Weitong Chen, Hanlin Wang, Kai Yu, Xin Peng, and Yiling Lou. 2024. TRANSAGENT: An LLM-Based Multi-Agent System for Code Translation. arXiv preprint arXiv:2409.19894 (2024).