GPT-3.5 for Code Review Automation: How Do Few-Shot Learning, Prompt Design, and Model Fine-Tuning Impact Their Performance?

Chanathip Pornprasit^a, Chakkrit Tantithamthavorn^{a,*}

^aMonash University, Australia

Abstract

Context: Recently, several large language models (LLMs)—the large pre-trained models based on the transformer architecture—were proposed. Prior studies in the natural language processing field and software engineering field conducted experiments focusing on different approaches to leveraging LLMs for downstream tasks. However, the existing literature still lacks the study of different

proposed. Prior studies in the natural language processing neur and software engineering flower consideration approaches to leveraging LLMs for downstream tasks. However, the existing literature still lacks the study of different approaches to leveraging GPT-3.5 (e.g., prompt engineering, few-shot learning and model fine-tuning) for the code review automation task (i.e., automatically generating improved code from submitted code). Thus, little is known about how GPT-3.5 should be leveraged for this task.

Objective: Our work aims to investigate the impact of few-shot learning, prompt design (i.e., using a persona pattern), and model fine-tuning on GPT-3.5.

Method: To conduct experiments, we design our prompt, perform few-shot learning with GPT-3.5 and fine-tune GPT-3.5 on a small training set.

Results: Through the experimental study of the three code review automation datasets, we find that (1) when few-shot learning is performed, GPT-3.5 achieves at least 46.38% higher Exact Match and at least 3.97% higher CodeBLEU than GPT-3.5 that zero-shot learning is performed, and (4) fine-tuned GPT-3.5 achieves at least 11.48% higher Exact Match and 0.15% lower CodeBLEU than when persona is not included in input prompts, (3) fine-tuned GPT-3.5 achieves at least 9.74% higher Exact Match and 0.12% higher CodeBLEU than GPT-3.5 for code review automation approaches.

Conclusions: Based on our experiment results, we recommend that when using GPT-3.5 for code review automation (1) few-shot learning should be performed rather than zero-shot learning. (2) persona should not be included when constructing prompts, and (3) GPT-3.5 should be fine-tuned by using a small training dataset.

Keywords: Modern Code Review, Code Review Automation, Large Language Model, GPT-3.5, few-Shot Learning, Persona

1. Introduction

Recently, large language models (LLMs)—large deep learning in performed. Another example is Browning should be performed tather than zero-shot learning in performed. Another example is Browning should be greated to the

open-source LLM that is based on LLaMa-2 model [3] further trained with source code.

Prior studies conducted experiments focusing on different approaches to leverage LLMs (e.g., prompt engineering [6, 7, 8], few-shot learning [9, 10, 11] and model fine-tuning [12, 13, 14]) for downstream tasks. For instance, Arora et al. [7] proposed the prompt design based on the question-answering

17, 18] were proposed. For example, Deligiannis et al. [15] proposed ChatGPT-based approach for fixing compilation errors in Rust. Prior work [19, 20, 21] also conducted empirical studies of LLMs on different software engineering tasks. For instance, Schäfer et al. [21] investigated the performance of GPT-3.5 for automated unit test generation in Javascript. However, the existing literature still lacks the study of different approaches to leveraging GPT-3.5 (e.g., prompt engineering [6, 7, 8], fewshot learning [9, 10, 11] and model fine-tuning [12, 13, 14]) for code review automation (i.e., automatically generating improved code from submitted code) [22, 23, 24]. Thus, little is known about how GPT-3.5 should be leveraged for the code

^{*}Corresponding author.

 $^{{\}it Email addresses:} \ {\tt chanathip.pornprasit@monash.edu}\ ({\tt Chanathip}$ Pornprasit), chakkrit@monash.edu (Chakkrit Tantithamthavorn)

review automation task.

In this work, we conduct the experimental study to investigate the impact of few-shot learning, prompt design, and model fine-tuning on GPT-3.5 for the code review automation task. In particular, to perform few-shot learning, we obtain examples from BM25 [25], and investigate the impact of the persona prompt pattern [26]. We also compare the performance of GPT-3.5 with the existing deep learning-based code review automation approaches [22, 23, 24] with respect to the following evaluation measures: Exact Match (EM) [24, 27] and Code-BLEU [28]. Through the experimental study of the three code review automation datasets (i.e., Tufano_{data} [22], D-ACT_{data} [24] and CodeReviewer_{data} [23]), we answer the following four research questions:

(RQ1) What is the impact of few-shot learning on GPT-3.5 for the code review automation task?

Result. When few-shot learning is performed, GPT-3.5 achieves at least 46.38% higher EM and at least 3.97% higher CodeBLEU than GPT-3.5 that zero-shot learning is performed. The increase in Exact Match and CodeBLEU is due to providing example input/output pairs in input prompts to GPT-3.5 to learn how to generate improved code.

(RQ2) What is the impact of the persona prompt pattern on GPT-3.5 for the code review automation task?

Result. When persona is included in input prompts to generate improved code, GPT-3.5 achieves at least 1.02% lower EM and 0.15% lower CodeBLEU than when persona is not included in the input prompts. The decrease in Exact Match and CodeBLEU is due to persona decreasing the likelihood of GPT-3.5 generating more correct and similar improved code to actual improved code.

(RQ3) What is the impact of the model fine-tuning on GPT-3.5 for the code review automation task?

Result. Fine-tuned GPT-3.5 achieves at least 9.74% higher EM and 0.12% higher CodeBLEU than GPT-3.5 that zero-shot and few-shot learning is performed. The increase in Exact Match and CodeBLEU is due to GPT-3.5 being fine-tuned with thousands of samples in a training dataset to learn how to generate improved code.

(RQ4) How does GPT-3.5 perform when compared to the existing code review automation approaches?

Result. The existing code review automation approaches achieve at least 5.47% higher EM than GPT-3.5 that zero-shot learning is performed while fine-tuned GPT-3.5 achieves at least 11.48% higher EM than the existing code review automation approaches.

Recommendation. Based on our experiment results, we recommend that when using GPT-3.5 for code review automation (1) few-shot learning should be performed rather than zero-shot learning, (2) persona should not be included when constructing prompts, and (3) GPT-3.5 should be fine-tuned by using a small training dataset.

Contributions. In summary, the main contributions of our work are as follows:

 We are the first to conduct experiments to investigate the impact of few-shot learning, prompt design, and model fine-tuning on GPT-3.5 for the code review automation tasks

 We provide recommendations for adapting GPT-3.5 for code review automation.

Open Science. To facilitate future work, we make the script, the dataset, and the output generated by GPT-3.5 available online¹. Our supplementary material will be made available upon acceptance.

Paper Organization. Section 2 describes the background with respect to the literature. Section 3 describes the study design of our study. Section 4 describes the experiment setup. Section 5 presents the experiment results. Section 6 discusses our experiment results. Section 7 describes possible threats to the validity. Section 8 draws the conclusions of our work.

2. Background

In this section, we provide an overview of GPT-3.5, fewshot learning, prompt engineering, model fine-tuning, and the existing code review automation approaches.

2.1. GPT 3.5

GPT 3.5 is a large generative model pre-trained on natural language and source code, consisting of approximately 175 billion parameters. Different from the existing pre-trained language models, GPT 3.5 is pre-trained by using Reinforcement Learning from Human Feedback (RLHF) [29], which involves humans providing feedback to improve the quality of the output that GPT 3.5 generates.

Recently, Qin *et al.* [30] show that GPT 3.5 is capable of various natural language processing tasks (e.g., question answering [31, 32, 33] and text summarization [34, 35]). Prior work [36] also showed that GPT 3.5 could be used for various software engineering tasks (e.g., vulnerability prediction [37, 38, 39] and commit message generation [40, 41, 42]). Generally, previous studies found that GPT-3.5 can be leveraged by performing few-shot learning [9, 10], engineering input prompts [6, 7, 8], and fine-tuning models [12, 13, 14]. We explain each approach to leveraging GPT-3.5 in the below sections.

2.2. Few-shot Learning

Few-shot learning [9, 10] is a learning approach by providing example input/output pairs and an input to an LLM to generate an output. Generally, the generation of an output y is conditioned on the context $C = \{(x_1, y_1), (x_2, y_2), ..., (x_k, y_k)\}$ which includes k examples, and the input x. The generation of y corresponding to x can be expressed as:

$$LLM(y|C,x) = \prod_{t=1}^{T} p(y_t|C,x,y_{< t})$$

Few-shot learning is widely studied in both NLP [9, 10, 11] and software engineering [43, 44, 15, 19]. However, little is

 $^{^{1}}https://shorturl.at/fpR28\\$

known about whether few-shot learning is suitable for code review automation tasks. To fill this gap, we formulate the following research question:

(RQ1) What is the impact of few-shot learning on GPT-3.5 for the code review automation task?

2.3. Prompt Engineering

Prompt engineering is the process of designing a prompt for LLMs so that LLMs can achieve the highest performance on downstream tasks [45]. Generally, a prompt consists of the following core components: instruction and input. An instruction indicates the action that a model has to perform on the given input. To design an effective prompt, OpenAI provides numerous recommendations² such as writing detailed instructions or adapting persona prompt pattern (i.e., specifying the personality of a model) [26].

Recent work [6, 7, 8] conducted empirical studies of prompt design on different NLP tasks. In addition, White *et al.* [46] presented various prompt patterns, including a persona prompt pattern, to automate software engineering tasks with ChatGPT. However, to the best of our knowledge, it is still unclear whether a persona prompt pattern should be included when constructing prompts for code review automation tasks. To fill this gap, we formulate the following research question:

(RQ2) What is the impact of the persona prompt pattern on GPT-3.5 for the code review automation task?

2.4. Model Fine-Tuning

Model fine-tuning is training a pre-trained model with a labelled dataset that consists of pairs of input sequences and corresponding labels [47]. Prior work [12, 13, 14] conducted empirical studies of model fine-tuning on NLP and software engineering tasks. For example, Chen *et al.* [14] conducted an experimental study of an LLM (i.e., GPT-3) fine-tuned on source code. However, little is known whether model fine-tuning could help GPT-3.5 to achieve higher performance for code review automation task. To fill this gap, we formulate the following research question:

(RQ3) What is the impact of the model fine-tuning on GPT-3.5 for the code review automation task?

2.5. Code Review Automation Approaches

Recent studies proposed several NMT-based code review automation approaches to facilitate patch authors revising their submitted patches. For example, Pornprasit *et al.* [24] proposed D-ACT, which leverages CodeT5 [48] and code difference. Tufano *et al.* [22] presented a pre-trained T5 model [49] to address the limitations in the previous work [50] (we will call this model *TufanoT5* henceforth). Similarly, Li *et al.* [23] proposed CodeReviewer, a pre-trained model that is based on the CodeT5 [48] model.

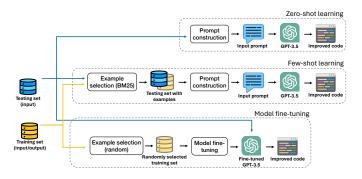


Figure 1: An overview of our study design.

While previous work showed that GPT-3.5 outperforms the existing approaches for different software engineering tasks [16, 51, 21], little is known about the capabilities of GPT-3.5 when compared to the above code review automation approaches. To fill this gap, we formulate the following research question:

(RQ4) How does GPT-3.5 perform when compared to the existing code review automation approaches?

3. Study Design

In this section, we explain the overview of our study design, the prompt design, zero-shot learning, few-shot learning and model fine-tuning.

3.1. Overview of Our Study Design

Figure 1 shows an overview of our study design. We perform zero-shot learning, perform few-shot learning, and finetune GPT-3.5 to generate improved code (i.e., code after being revised) from a given submitted code (and a reviewer comment if available). We choose GPT-3.5 in our study since GPT-3.5 is trained by using Reinforcement Learning from Human Feedback (RLHF) [29] to ensure that the generated output has high quality. To perform zero-shot learning with GPT-3.5, we ask GPT-3.5 to generate the improved code from the given input prompts. To perform few-shot learning with GPT-3.5, we first construct input prompts from the test samples and their selected demonstration examples. Then, we ask GPT-3.5 to generate the improved code from the given input prompts. Finally, for fine-tuning GPT-3.5, we use the selected training examples to fine-tune GPT-3.5. Then, we ask fine-tuned GPT-3.5 to generate the improved code from a given submitted code and a reviewer's comment (if available). In the below sections, we explain how we design prompt templates for GPT-3.5, perform zero-shot learning and few-shot learning with GPT-3.5, and fine-tune GPT-3.5 in detail.

3.2. Prompt Design

In our study, we design the prompt templates for performing zero-shot learning and few-shot learning with GPT-3.5 by fol-

 $^{^2} https://platform.openai.com/docs/guides/prompt-engineering \\$

Table 1: A statistic of the studied datasets (the dataset of Android, Google and Ovirt are from D-ACT_{data} [24]).

Dataset	# Train	# Validation	# Test	# Language	Granularity	Has Comment
CodeReviewer _{data} [23]	150,405	13,102	13,104	9	Diff Hunk	Yes
Tufano _{data} [22]	134,238	16,779	16,779	1	Function	Yes/No
Android [24]	14,690	1,836	1,835	1	Function	No
Google [24]	9,899	1,237	1,235	1	Function	No
Ovirt [24]	21,509	2,686	2,688	1	Function	No

(Persona) You are an expert software developer in < lang>. You always want to improve your code to have higher quality.

(Instruction) Your task is to improve the given submitted code based on the given reviewer comment. Please only generate the improved code without your explanation.

(Innut) <innut code

(Optional Input) // <input comment>

(a) A prompt template for zero-shot learning (when a reviewer comment is available).

(Persona) You are an expert software developer in < lang>. You always want to improve your code to have higher quality.

(Instruction) Your task is to improve the given submitted code. Please only generate the improved code without your explanation.

(Input) <input code>

(b) A prompt template for zero-shot learning (when a reviewer comment is not available).

(Persona) You are an expert software developer in < lang>. You always want to improve your code to have higher quality. You have to generate an output that follows the given examples.

(Instruction and examples) You are given 3 examples. Each example begins with "##Example" and ends with "---". Each example contains the submitted code, the developer comment, and the improved code. The submitted code and improved code is written in <lang>. Your task is to improve your submitted code based on the comment that another developer gave you.

Example

Submitted code: <code>

Developer comment: <comment>

Improved code: <code>

<other examples>

(Input) Submitted code: <input code>

(Input) Developer comment: <input comment>

(c) A prompt template for few-shot learning (when a reviewer comment is available).

(Persona) You are an expert software developer in <lang>. You always want to improve your code to have higher quality. You have to generate an output that follows the given examples.

(Instruction and examples) You are given 3 examples. Each example begins with "##Example and ends with "---". Each example contains the submitted code and the improved code. The submitted code and improved code is written in <lang>. Your task is to improve your submitted code.

Example

Submitted code: <code>

<nther examples>

--

(Input) Submitted code: <input code>

(d) A prompt template for few-shot learning (when a reviewer comment is not available).

Figure 2: Prompt templates for performing zero-shot learning and few-shot learning with GPT-3.5 (*lang* refers to a programming language).

lowing the guidelines from OpenAI³⁴ to ensure that the struc-

ture of the prompt is suitable for GPT-3.5. In particular, the prompt template for zero-shot learning (as depicted in Figure 2a and Figure 2b) consists of the following components: persona [26], instruction and input (i.e., submitted code). The input also includes a reviewer comment if available. On the other hand, the prompt template for few-shot learning (as depicted in Figure 2c and Figure 2d) consists of components similar to the ones in the prompt template for zero-shot learning, and a set of input (i.e., submitted code and a reviewer comment) and output (i.e., improved code) example pairs. We include persona in both prompt templates to instruct GPT-3.5 to act as a software developer. We do so to ensure that the improved code generated by GPT-3.5 looks like the source code written by a software developer. For the prompt template for few-shot learning, we provide a set of example pairs to help GPT-3.5 adapt to the new task that it has never learned before.

3.3. Zero-Shot Learning

To perform zero-shot learning with GPT-3.5, we construct input prompts from the prompt template in Figure 2a and the code submitted for review with a reviewer comment in the testing set. However, in case a reviewer comment is not available, we construct input prompts from the prompt template in Figure 2b and the code submitted for review instead. Then, we ask GPT-3.5 to generate the improved code from a given input prompt.

3.4. Few-Shot Learning

To perform few-shot learning with GPT-3.5, we first obtain three example pairs of input and output from the training set by using BM25 [25] provided by the gensim⁵ package. We do so since prior work [52, 53] shows that BM25 [25] can outperform other sample selection approaches. Then, we construct input prompts from the prompt template in Figure 2c, the code submitted for review and reviewer comment in the testing set, and its corresponding selected examples. In case a reviewer comment is not available, we construct input prompts from the prompt template in Figure 2d, the code submitted for review in the testing set, and its corresponding selected examples instead. After that, we ask GPT-3.5 to generate the improved code from a given input prompt.

³https://help.openai.com/en/articles/6654000-best-practices-for-prompt-engineering-with-openai-api

⁴https://platform.openai.com/docs/guides/prompt-engineering/strategywrite-clear-instructions

⁵https://github.com/piskvorky/gensim

3.5. Fine-Tuning GPT-3.5

To fine-tune GPT-3.5, we first randomly select approximately 6% of total input/output pairs from the training dataset. We do not use the whole training set to fine-tune GPT-3.5 since it is prohibitively expensive. Then, we use the selected training examples to fine-tune GPT-3.5 by using the API provided by OpenAI⁶. After that, we ask the fine-tuned GPT-3.5 to generate the improved code from a given submitted code and a reviewer comment (if available).

4. Experiment Setup

In this section, we explain the detail of the datasets, hyperparameter setting of GPT-3.5, and evaluation measures in our experiment.

4.1. Dataset

In this study, we use the following datasets which are summarized in Table 1: Tufano_{data} [22], D-ACT_{data} [24] and Code-Reviewer_{data} [23]. We describe the details of these datasets below

- CodeReviewer_{data}: Li *et al.* [23] collected this dataset from the GitHub projects across nine programming languages (i.e., C, C++, C#, Java, Python, Ruby, php, Go, and Javascript). The dataset contains triplets of the current version of code (diff hunk granularity), the reviewers' comment, and the revised version of code (diff hunk granularity).
- Tufano_{data}: Tufano *et al.* [22] collected this dataset from Java projects in GitHub containing at least 50 pull requests, and 6,388 Java projects hosted in Gerrit. Each record in the dataset contains a triplet of code submitted for review (function granularity), a reviewer's comment, and code after being revised (function granularity). Tufano *et al.* [22] created two types of this dataset (i.e., Tufano_{data} (with comment) and Tufano_{data} (without comment)).
- **D-ACT**_{data}: Pornprasit *et al.* [24] collected this dataset from the three Java projects hosted on Gerrit (i.e., Android, Google and Ovirt). Each record in the dataset contains a triplet of codebase (function granularity), code of the first version of a patch (function granularity), and code of the approved version of a patch (function granularity).

4.2. Hyper-Parameter Setting

In this study, we use the following hyper-parameter settings when using GPT-3.5 to generate improved code: temperature of 0.0 (as suggested by Guo *et al.* [54]), top_p of 1.0 (default value), and max length of 512. For model fine-tuning, we use hyper-parameters (e.g., number of epochs and learning rate) that are automatically selected by OpenAI API.

4.3. Evaluation Measure

We use the following evaluation measures in our experiment:

- 1. Exact Match (EM) [23, 24, 27] is the number of the generated improved code that is the same as the actual improved code in the testing dataset. We use this measure since it is widely used for evaluating code review automation approaches [22, 24, 27]. To compare the generated improved code with the actual improved code, we first tokenize both improved code to sequences of tokens. Then, we compared the sequence of tokens of the generated improved code with the sequence of tokens of the actual improved code. A high value of EM indicates that a model can generate improved code that is the same as the actual improved code in the testing dataset.
- 2. CodeBLEU [28] is the extended version of BLEU (i.e., an n-gram overlap between the translation generated by a deep learning model and the translation in ground truth) [55] for automatic evaluation of the generated code. We do not measure BLEU like in prior work [22, 23] since Ren et al. [28] found that this measure ignores syntactic and semantic correctness of the generated code. In addition to BLEU, CodeBLEU considers the weighted n-gram match, matched syntactic information (i.e., abstract syntax tree: AST) and matched semantic information (i.e., data flow: DF) when computing the similarity between the generated improved code and the actual improved code. A high value of CodeBLEU indicates that a model can generate improved code that is syntactically and semantically similar to the actual improved code in the testing dataset.

5. Result

In this section, we present the experiment results of the follwing four research questions.

(RQ1) What is the impact of few-shot learning on GPT-3.5 for the code review automation task?

Approach. To address this RQ, we use the prompts in Figure 2 by not including persona to enable GPT-3.5 to perform zeroshot and few-shot learning as explained in Section 3. Then, we measure EM and CodeBLEU of the results obtained from GPT-3.5. GPT-3.5 that zero-shot learning and few-shot learning is performed is denoted as GPT-3.5_{Zero-shot} and GPT-3.5_{Few-shot}, respectively.

Result. When few-shot learning is performed, GPT-3.5 achieves at least 46.38% higher EM and at least 3.97% higher CodeBLEU than GPT-3.5 that zero-shot learning is performed. Table 2 shows the evaluation results of GPT-3.5_{Zero-shot} and GPT-3.5_{Few-shot} in terms of EM and CodeBLEU. The table shows that GPT-3.5_{Few-shot} achieves at least 46.38% higher EM than GPT-3.5_{Zero-shot}. The table also shows that GPT-3.5_{Few-shot} achieves 3.97% - 33.36% higher CodeBLEU than GPT-3.5_{Zero-shot}. Figure 3a - Figure 3d show the Venn diagram of the improved code that GPT-3.5_{Zero-shot} and GPT-3.5_{Few-shot} correctly generate. The figures show that the number of improved code that

⁶https://platform.openai.com/docs/guides/fine-tuning/create-a-fine-tuned-model

Table 2: (RQ1) The evaluation results of GPT-3.5 when zero-shot learning and few-shot learning is performed.

A 1	CodeReviewer _{data}		Tufano _{data} (with comment)		Tufano _{data} (without comment)		Android		Google		Ovirt	
Approach	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU
GPT-3.5 _{Zero-shot}	17.72%	44.17%	13.52%	78.36%	2.62%	74.92%	0.49%	61.85%	0.16%	61.04%	0.48%	56.55%
GPT-3.5 _{Few-shot}	26.55%	47.50%	19.79%	81.47%	8.96%	79.21%	2.34%	75.33%	2.89%	81.40%	1.64%	73.83%

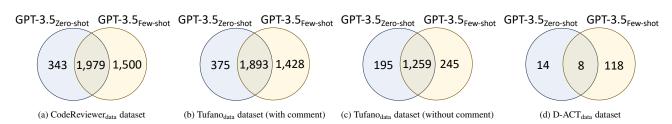


Figure 3: (RQ1) Venn diagrams showing EM achieved by GPT-3.5_{Zero-shot} and GPT-3.5_{Few-shot}.

only GPT-3.5 $_{\text{Few-shot}}$ correctly generates is at least 280.8% higher than GPT-3.5 $_{\text{Zero-shot}}$.

The results indicate that performing few-shot learning with GPT-3.5 could help GPT-3.5 to generate more correct and similar improved code to actual improved code compared to performing zero-shot learning with GPT-3.5. The reason for this indication is that GPT-3.5 learns to generate improved code from given example input/output pairs in an input prompt. Such example input/output pairs in an input prompt could help GPT-3.5 to adapt to the code refinement task that it never learns during the model pre-training phase. In contrast, when zero-shot learning is performed with GPT-3.5, GPT-3.5 has to rely on what it learned during the model pre-training phase, which is not specific to the code refinement task. Thus, GPT-3.5 has to rely on what it learned during the model pre-training phase, which is not specific to the code refinement task.

(RQ2) What is the impact of the persona prompt pattern on GPT-3.5 for the code review automation task?

Approach. To address this RQ, we use the prompts in Figure 2 by including persona to enable GPT-3.5 to perform zeroshot and few-shot learning as explained in Section 3. GPT-3.5_{Zero-shot} and GPT-3.5_{Few-shot} that generate improved code from the prompts with persona are denoted as GPT-3.5-WP_{Zero-shot} and GPT-3.5-WP_{Few-shot}, respectively. Similarly, GPT-3.5_{Zero-shot} and GPT-3.5_{Few-shot} that generate improved code from the prompts without persona are denoted as GPT-3.5-NP_{Zero-shot} and GPT-3.5-NP_{Few-shot}, respectively.

Result. When persona is included in input prompts to generate improved code, GPT-3.5 achieves at least 1.02% lower EM and 0.15% lower CodeBLEU than when persona is not included in the input prompts. Table 3 shows the evaluation results of GPT-3.5 that zero-shot learning is performed by using input prompts with and without persona. The table shows that GPT-3.5-WP_{Zero-shot} achieves at least 3.67% and 1.33% lower EM and CodeBLEU than GPT-3.5-NP_{Zero-shot}, respectively. Figure 4a - Figure 4d show the Venn diagram of the improved code that GPT-3.5-WP_{Zero-shot} and GPT-3.5-NP_{Zero-shot} correctly generate. The figures show that the number of improved code that only GPT-3.5-WP_{Zero-shot} correctly generates is at least 22.02% lower than GPT-3.5-NP_{Zero-shot}

Table 4 shows the evaluation results of GPT-3.5 that few-

shot learning is performed by using input prompts with and without persona. The table shows that GPT-3.5-WP_{Few-shot} achieves at least 1.02% and 0.15% lower EM and CodeBLEU than GPT-3.5-NP_{Few-shot}, respectively. However, we observe that for the Tufano_{data} dataset, GPT-3.5-WP_{Few-shot} achieves 1.21% - 2.46% higher EM than GPT-3.5-NP_{Few-shot}. Figure 5a - Figure 5d show the Venn diagram of the improved code that GPT-3.5-WP_{Few-shot} and GPT-3.5-NP_{Few-shot} correctly generate. The figures show that the number of improved code that only GPT-3.5-WP_{Few-shot} correctly generates is at least 16.48% lower than GPT-3.5-NP_{Few-shot}. Nevertheless, for the Tufano_{data} dataset, the number of improved code that only GPT-3.5-WP_{Few-shot} correctly generates is 20.1% - 26.06% higher than GPT-3.5-NP_{Few-shot}.

The above results indicate that including persona in input prompts when performing zero-shot and few-shot learning does not guarantee that GPT-3.5 could generate more correct and similar improved code to actual improved code. The reason for this indication is that when persona is included in input prompts, GPT-3.5 is instructed to generate source code like how a software developer would do. In a zero-shot learning scenario, having persona in input prompts tends to decrease the likelihood of GPT-3.5 generating more correct and similar improved code to actual improved code. On the contrary, in a few-shot learning scenario, having persona in input prompts does not always increase the likelihood of GPT-3.5 generating more correct and similar improved code to actual improved code like in zero-shot learning.

(RQ3) What is the impact of the model fine-tuning on GPT-3.5 for the code review automation task?

Approach. To address this RQ, we fine-tune GPT-3.5 as explained in Section 3. Then, similar to RQ1 and RQ2, we measure EM and CodeBLEU of the results obtained from the fine-tuned GPT-3.5 (the fine-tuned GPT-3.5 models are denoted as GPT-3.5_{Fine-tuned}). In addition, we analyze the improved code that GPT-3.5_{Zero-shot}, GPT-3.5_{Few-shot} and GPT-3.5_{Fine-tuned} correctly generate to understand the characteristics of code changes of such improved code. To do so, we randomly select the improved code that is only correctly generated by a particular model (e.g., we randomly obtain the improved code that only GPT-3.5_{Zero-shot} correctly generates while the others do not.) by using the confidence level of 95% and the confidence interval

Table 3: (RQ2) The evaluation results GPT-3.5_{Zero-shot} (persona is included and not included in input prompts).

A	CodeReviewer _{data}		Tufano _{data} (with comment)		Tufano _{data} (without comment)		Android		Google		Ovirt	
Approach	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU
GPT-3.5-WP _{Zero-shot}	17.07%	43.11%	12.49%	77.32%	2.29%	73.21%	0.57%	55.88%	0.00%	50.65%	0.22%	45.73%
GPT-3.5-NP _{Zero-shot}	17.72%	44.17%	13.52%	78.36%	2.62%	74.92%	0.49%	61.85%	0.16%	61.04%	0.48%	56.55%

Table 4: (RQ2) The evaluation results of GPT-3.5_{Few-shot} (persona is included and not included in input prompts).

A	CodeReviewer _{data}		Tufano _{data} (with comment)		Tufano _{data} (without comment)		Android		Google		Ovirt	
Approach	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU
GPT-3.5-WP _{Few-shot}	26.28%	47.43%	20.03%	81.61%	9.18%	78.98%	1.62%	74.65%	2.45%	81.07%	1.67%	73.29%
GPT-3.5-NP _{Few-shot}	26.55%	47.50%	19.79%	81.47%	8.96%	79.21%	2.34%	75.33%	2.89%	81.40%	1.64%	73.83%

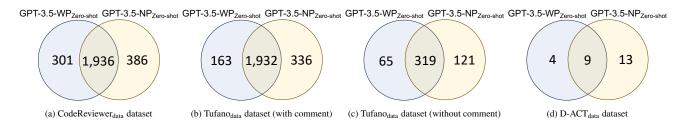


Figure 4: (RQ2) Venn diagrams showing EM achieved by GPT-3.5-WPZero-shot and GPT-3.5-NPZero-shot.

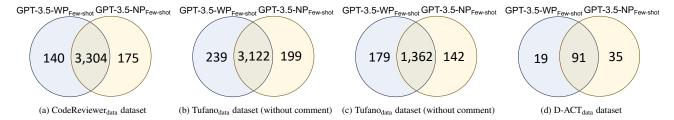


Figure 5: (RQ2) Venn diagrams showing EM achieved by GPT-3.5-WP_{Few-shot} and GPT-3.5-NP_{Few-shot}.

of 5%. Then, we classify the code change of the selected improved code into three categories (i.e., *fixing bug*, *refactoring* and *other*) by following the taxonomy of code change created by Tufano *et al.* [27].

Result. Fine-tuned GPT-3.5 achieves at least 9.74% higher EM and 0.12% higher CodeBLEU than GPT-3.5 that zeroshot and few-shot learning is performed. Table 5 shows the evaluation results of GPT-3.5_{Zero-shot}, GPT-3.5_{Few-shot} and GPT-3.5_{Fine-tuned} that generate improved code from input prompts with persona. The table shows that GPT-3.5_{Fine-tuned} achieves at least 75.98% and 9.74% higher EM than GPT-3.5_{Zero-shot} and GPT-3.5_{Few-shot}, respectively. However, for the Tufano_{data} (without comment) dataset, we observe that GPT-3.5_{Few-shot} achieves 51.99% higher EM than GPT-3.5_{Fine-tuned}. The table also shows that GPT-3.5_{Fine-tuned} achieves at least 7.4% and 0.12% higher CodeBLEU than GPT-3.5_{Zero-shot} and GPT-3.5_{Few-shot}, respectively.

Table 6 shows the evaluation results of GPT- $3.5_{Zero-shot}$, GPT- $3.5_{Few-shot}$ and GPT- $3.5_{Fine-tuned}$ that generate improved code from input prompts without persona. The table shows that GPT- $3.5_{Fine-tuned}$ achieves at least 63.91% and 11.98% higher EM than GPT- $3.5_{Zero-shot}$ and GPT- $3.5_{Few-shot}$, respectively. However, for the Tufano_{data} (without comment), we observe that GPT- $3.5_{Few-shot}$ achieves 48.84% higher EM than GPT- $3.5_{Fine-tuned}$. The table also shows that GPT- $3.5_{Fine-tuned}$ achieves at least 5.91%

and 1.14% higher CodeBLEU than GPT-3.5 $_{\rm Zero\text{-}shot}$ and GPT-3.5 $_{\rm Few\text{-}shot}$, respectively.

Finally, we show the characteristic of the code changes (i.e., fixing bug, refactoring and other) of the improved code that GPT-3.5 $_{\rm Zero\text{-}shot}$, GPT-3.5 $_{\rm Few\text{-}shot}$ and GPT-3.5 $_{\rm Fine\text{-}tuned}$ correctly generate in Figure 6a and Figure 6b. The figures show that for the Tufano_{data}(with comment), CodeReviewer_{data} and D-ACT_{data}, GPT-3.5 $_{\rm Fine\text{-}tuned}$ achieves the highest EM for the code changes of *Refactoring* and *Other*. However, for the Tufano_{data} (without comment) dataset, GPT-3.5 $_{\rm Few\text{-}shot}$ achieves the highest EM for the code changes of all categories.

The above results indicate that in overall, model fine-tuning could help GPT-3.5 to generate more correct improved code and generate more similar improved code to actual improved code than GPT-3.5 that zero-shot learning and few-shot learning is performed. The reason for this indication is that when GPT-3.5 is fine-tuned, it directly learns how to generate improved code from a given input code (and comment if available) from thousands of examples in a training set. Different from model fine-tuning, GPT-3.5 has no additional information to learn how improved code is generated when zero-shot learning is performed. On the other hand, when few-shot learning is performed, GPT-3.5 has only a few examples to learn how improved code is generated.

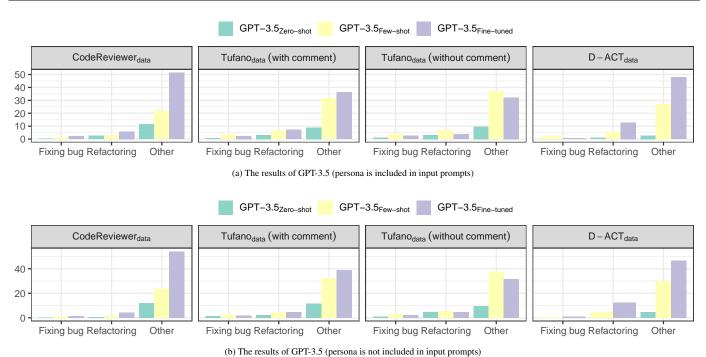
(RQ4) How does GPT-3.5 perform when compared to the

 $Table \ 5: (RQ3) \ The \ evaluation \ results \ of \ GPT-3.5_{Ero-shot}, \ GPT-3.5_{Few-shot}, \ and \ GPT-3.5_{Fine-tuned} \ (persona\ is \ included\ in\ input\ prompts).$

A	CodeReviewer _{data}		Tufano _{data} (with comment)		Tufano _{data} (without comment)		Android		Google		Ovirt	
Approach	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU
GPT-3.5 _{Zero-shot}	17.07%	43.11%	12.49%	77.32%	2.29%	73.21%	0.57%	55.88%	0.00%	50.65%	0.22%	45.73%
GPT-3.5 _{Few-shot}	26.28%	47.43%	20.03%	81.61%	9.18%	78.98%	1.62%	74.65%	2.45%	81.07%	1.67%	73.29%
GPT-3.5 _{Fine-tuned}	37.70%	49.20%	21.98%	83.04%	6.04%	79.76%	2.29%	74.74%	6.14%	81.02%	2.64%	74.95%

Table 6: (RQ3) The evaluation results of GPT-3.5_{Zero-shot}, GPT-3.5_{Few-shot}, and GPT-3.5_{Fine-tuned} (persona is not included in input prompts).

A 1	CodeReviewer _{data}		Tufano _{data} (with comment)		Tufano _{data} (without comment)		Android		Google		Ovirt	
Approach	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU
GPT-3.5 _{Zero-shot}	17.72%	44.17%	13.52%	78.36%	2.62%	74.92%	0.49%	61.85%	0.16%	61.04%	0.48%	56.55%
GPT-3.5 _{Few-shot}	26.55%	47.50%	19.79%	81.47%	8.96%	79.21%	2.34%	75.33%	2.89%	81.40%	1.64%	73.83%
GPT-3.5 _{Fine-tuned}	37.93%	49.00%	22.16%	82.99%	6.02%	79.81%	2.34%	74.15%	6.71%	81.08%	3.05%	74.67%



 $Figure \ 6: (RQ3) \ The \ EM \ achieved \ by \ GPT-3.5_{Zero-shot}, \ GPT-3.5_{Few-shot} \ and \ GPT-3.5_{Fine-tuned} \ categorized \ by \ types \ of \ code \ change.$

existing code review automation approaches?

Approach. To address this RQ, we compare GPT-3.5_{Zero-shot}, GPT-3.5_{Few-shot} and GPT-3.5_{Fine-tuned} with the existing code review automation approaches (i.e., TufanoT5 [22], D-ACT [24] and CodeReviewer [23]). To do so, we select the results of GPT-3.5_{Zero-shot}, GPT-3.5_{Few-shot} and GPT-3.5_{Fine-tuned} that is generated from input prompts without persona. We select such results since they achieve higher EM and CodeBLEU than the ones that are generated from input prompts with persona (as shown in RQ2). Then, we obtain the results of the existing code review automation approaches. In particular, we obtain the results of TufanoT5 and D-ACT from the replication packages. However, since Li et al. [23] do not make their results publicly available, we obtain the results from Guo et al. [54] instead. Similar to RQ1-RQ3, we measure EM and CodeBLEU of the results obtained from GPT-3.5 and the existing code review automation approaches.

Result. The existing code review automation approaches achieve at least 5.47% higher EM than GPT-3.5 that zero-

shot learning is performed while fine-tuned GPT-3.5 achieves at least 11.48% higher EM than the existing code review automation approaches. Table 7 shows the results of GPT-3.5_{Zero-shot}, GPT-3.5_{Few-shot}, GPT-3.5_{Fine-tuned} and the existing code review automation approaches. The table shows that the existing code review automation approaches achieve at least 5.47% and 1.43% higher EM and CodeBLEU than GPT-3.5_{Zero-shot}, respectively, indicating that the existing code review automation approaches can generate more correct improved code and generate more similar improved code to actual improved code than performing zero-shot learning with GPT-3.5.

We observe from the table that in terms of EM, CodeReviewer and D-ACT achieve at least 9.15% higher than GPT-3.5_{Few-shot}. In contrast, GPT-3.5_{Few-shot} achieves at least 38.78% higher EM than TufanoT5. In terms of CodeBLEU, CodeReviewer and D-ACT achieve at least 0.55% higher than GPT-3.5_{Few-shot}. On the contrary, GPT-3.5_{Few-shot} achieves at least 2.5% higher CodeBLEU than TufanoT5. The results indicate that performing few-shot learning with GPT-3.5 does not al-

Table 7: (RO4) The evaluation results of GPT-3.5 and the existing code review au
--

	CodeR	CodeReviewer _{data}		Tufano _{data} (with comment)		Tufano _{data} (without comment)		Android		Google		Ovirt
	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU	EM	CodeBLEU
GPT-3.5 _{Zero-shot}	17.72%	44.17%	13.52%	78.36%	2.62%	74.92%	0.49%	61.85%	0.16%	61.04%	0.48%	56.55%
GPT-3.5 _{Few-shot}	26.55%	47.50%	19.79%	81.47%	8.96%	79.21%	2.34%	75.33%	2.89%	81.40%	1.64%	73.83%
GPT-3.5 _{Fine-tuned}	37.93%	49%	22.16%	82.99%	6.02%	79.81%	2.34%	74.15%	6.71%	81.08%	3.05%	74.67%
CodeReviewer	33.23%	55.43%	-	-	-	-	-	-	-	-	-	-
TufanoT5	-	-	14.26%	79.48	5.40%	77.26%	-	-	-	-	-	-
D-ACT	-	-	-	-	-	-	0.65%	75.99%	5.98%	81.85%	1.79%	79.77%

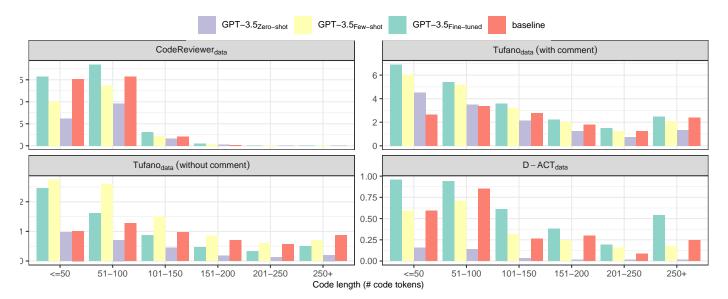


Figure 7: Exact Match categorized by the length of revised code. The baseline in the CodeReviewer $_{data}$, Tufano $_{data}$ and D-ACT $_{data}$ datasets are CodeReviewer, TufanoT5 and D-ACT, respectively.

ways help GPT-3.5 generate more correct and similar improved code to actual improved code than the existing code review automation approaches.

The table also shows that GPT-3.5_{Fine-tuned} achieves at least 12.21% higher EM than the existing code review automation approaches. However, CodeReviewer and D-ACT achieves at least 0.95% higher CodeBLEU than GPT-3.5_{Fine-tuned} while GPT-3.5_{Fine-tuned} achieves at least 3.3% higher CodeBLEU than TufanoT5. The results indicate that fine-tuning GPT-3.5 could help GPT-3.5 generate more correct improved code than the existing code review automation approaches.

6. Discussion

6.1. Recommendations

In case of using GPT-3.5 without fine-tuning, we recommend performing few-shot learning rather than zero-shot learning, and constructing prompts without including persona in input prompts when using GPT-3.5 for code review automation. We recommend doing so since the results of RQ1 show that few-shot learning could help GPT-3.5 generate more correct improved code than using zero-shot learning. In addition, the results of RQ2 show that when performing zero-shot and few-shot learning with GPT-3.5 by not including persona in input prompts, GPT-3.5 generates more correct improved code than

performing zero-shot and few-shot learning with GPT-3.5 by including persona in input prompts.

In case of fine-tuning GPT-3.5, we recommend using a few examples obtained from a training dataset to fine-tune GPT-3.5 when using GPT-3.5 for code review automation. We recommend doing so since the results of RQ3 show that GPT-3.5 that is fine-tuned by using around 6% of the training dataset can generate more correct improved code than GPT-3.5 that zero-shot and few-shot learning is performed. The results of RQ4 also show that fine-tuned GPT-3.5 can generate more correct improved code than the existing code review automation approaches [22, 23, 24].

6.2. The Characteristics of the Improved Code that are Correctly Generated

In RQ4, we measure Exact Match to show the number of improved code that is correctly generated. However, this measure does not explain the characteristics of improved code that GPT-3.5_{Zero-shot}, GPT-3.5_{Few-shot}, GPT-3.5_{Fine-tuned}, and the existing code review automation approaches [22, 23, 24] correctly generate. Thus, we further investigate the characteristic of the improved code that is correctly generated in terms of number of code tokens (as shown in Figure 7) and the number of changed tokens compared to the code submitted for review (as shown in Figure 8).

GPT-3.5_{Fine-tuned} achieves the highest EM for all numbers

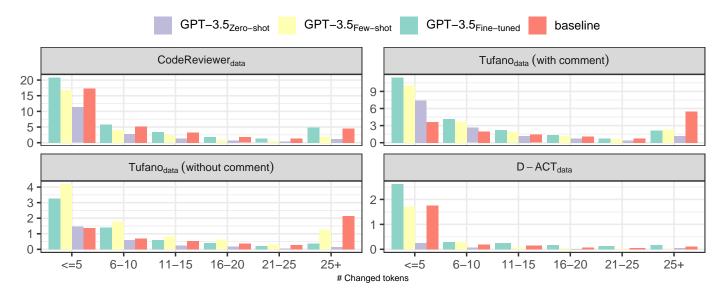


Figure 8: Exact Match categorized by the number of changed tokens. The baseline in the CodeReviewer_{data}, Tufano_{data} and D-ACT_{data} datasets are CodeReviewer, TufanoT5 and D-ACT, respectively.

of code tokens when compared to the existing code review automation approaches. Figure 7 shows EM achieved by GPT-3.5_{Zero-shot}, GPT-3.5_{Few-shot}, GPT-3.5_{Fine-tuned} and the existing code review automation approaches, categorized by the number of code tokens of improved code. The figure shows that for the CodeReviewer_{data}, Tufano_{data} (with comment) and D-ACT_{data} dataset, GPT-3.5_{Fine-tuned} achieves the highest EM for all numbers of code tokens. We also observe that CodeReviewer and D-ACT achieve higher EM than GPT-3.5_{Zero-shot} and GPT-3.5_{Few-shot} for all numbers of code tokens. However, for the Tufano_{data} (without comment) dataset, GPT-3.5_{Few-shot} achieves the highest EM for all numbers of code tokens.

GPT-3.5_{Fine-tuned} achieves the highest EM for all numbers of changed tokens when compared to the existing code review automation approaches. Figure 8 shows EM achieved by GPT-3.5_{Zero-shot}, GPT-3.5_{Few-shot}, GPT-3.5_{Fine-tuned} and the existing code review automation approaches, categorized by the number of changed tokens (i.e., tokens that are inserted, deleted or replaced when compared to the submitted code). The figure shows that for the CodeReviewer_{data}, Tufano_{data} (with comment) and D-ACT_{data} dataset, GPT-3.5_{Fine-tuned} achieves the highest EM for all numbers of changed tokens. In contrast, CodeReviewer and D-ACT achieve higher EM than GPT-3.5_{Zero-shot} and GPT-3.5_{Few-shot} for all numbers of changed tokens. On the other hand, for the Tufano_{data} (without comment) dataset, GPT-3.5_{Few-shot} achieves the highest EM for all numbers of changed tokens.

7. Threats to Validity

We describe the threats to the validity of our study below.

7.1. Threats to Construct Validity

Threats to construct validity relate to the example selection technique that we used to select examples for doing few-shot learning and fine-tuning GPT-3.5, and the design choices of our prompt. We explain each threat below.

In our study, we only use the BM25 [25] technique to select examples for doing few-shot learning, which is shown to be the most effective in prior studies [52, 53]. However, there are other example selection techniques in NLP that we do not explore. Such techniques may help GPT-3.5 outperforms the existing code review automation approaches. Thus, other sample selection techniques can be explored in future work.

In addition, we randomly select a subset of examples from a training set to fine-tune GPT-3.5. We do not use the whole training set since it is prohibitively expensive (i.e., it could cost more than thousands dollars to fine-tune a single model). The randomly selected examples may be sub-optimal for fine-tuning GPT-3.5. Therefore, future work could explore other approaches for selecting examples from a training set.

Another threat is the design choice of our prompts for zeroshot and few-shot learning. It is possible that the design of our prompt is sub-optimal. To mitigate this threat, we follow the guidelines of prompt design from OpenAI. However, future work could experiment with other prompt designs to find the most suitable prompts for code review automation.

7.2. Threats to Internal Validity

Threats to internal validity relate to the number of examples for each test sample, the randomness of GPT3.5, and the hyper-parameter settings that we use to fine-tune GPT-3.5. In this study, we only give three examples for each test sample, similar to prior work [19]. However, providing more examples to a test sample may help GPT-3.5 generates more correct improved code. In addition, the results that we obtain from GPT-3.5 may vary due to the randomness of GPT-3.5. However, doing the same experiments multiple rounds can be expensive due to large testing datasets. Finally, we do not explore all possible combinations of hyper-parameter settings (e.g., the

number of epoch or learning rate) when fine-tuning GPT-3.5. We do not do so since the search space of hyper-parameter settings is large, which can be expensive. Nonetheless, the main goal of this study is not to find the best hyper-parameter settings for code review automation, but to investigate the impact of few-shot learning, prompt design, and model fine-tuning on GPT-3.5 for the code review automation task.

7.3. Threats to External Validity

Threats to external validity relate to the generalizability of our findings in other software projects. In this study, we conduct the experiment with the dataset obtained from recent work [22, 23, 24]. However, the results of our experiment may not be generalized to other software projects. Thus, other software projects can be explored in future work.

8. Conclusion

In this work, we conduct an experimental study to investigate the impact of few-shot learning, prompt design, and model fine-tuning on GPT-3.5 for the code review automation task. We also compare the performance of GPT-3.5 with the existing code review automation approaches [22, 23, 24]. Our results show that (1) few-shot learning could help GPT-3.5 to generate more correct improved code than zero-shot learning, (2) including persona in input prompts mostly decreases the performance of GPT-3.5, (3) model fine-tuning could improve the performance of GPT-3.5 compared to performing zero-shot and few-shot learning with GPT-3.5, and (4) fine-tuning GPT-3.5 could help GPT-3.5 to outperform the existing code review automation approaches. Based on the experiment results, we recommend that when using GPT-3.5 for code review automation (1) few-shot learning should be performed rather than zero-shot learning, (2) persona should not be included when constructing input prompts, and (3) GPT-3.5 should be fine-tuned by using a small training dataset.

References

- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is All You Need. In *Proceedings of NIPS*, pages 5999–6009, 2017.
- [2] Baptiste Rozière, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, Jérémy Rapin, et al. Code llama: Open foundation models for code. arXiv preprint arXiv:2308.12950, 2023.
- [3] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. arXiv preprint arXiv:2307.09288, 2023.
- [4] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. arXiv preprint arXiv:2303.08774, 2023.
- [5] BigScience Workshop, Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, et al. Bloom: A 176bparameter open-access multilingual language model. arXiv preprint arXiv:2211.05100, 2022.

- [6] Albert Lu, Hongxin Zhang, Yanzhe Zhang, Xuezhi Wang, and Diyi Yang. Bounding the capabilities of large language models in open text generation with prompt constraints. arXiv preprint arXiv:2302.09185, 2023.
- [7] Simran Arora, Avanika Narayan, Mayee F Chen, Laurel Orr, Neel Guha, Kush Bhatia, Ines Chami, Frederic Sala, and Christopher Ré. Ask me anything: A simple strategy for prompting language models. arXiv preprint arXiv:2210.02441, 2022.
- [8] Sonish Sivarajkumar, Mark Kelley, Alyssa Samolyk-Mazzanti, Shyam Visweswaran, and Yanshan Wang. An empirical evaluation of prompting strategies for large language models in zero-shot clinical natural language processing. arXiv preprint arXiv:2309.08008, 2023.
- [9] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. Proceedings of NeurIPS, pages 1877–1901, 2020.
- [10] Jiachang Liu, Dinghan Shen, Yizhe Zhang, Bill Dolan, Lawrence Carin, and Weizhu Chen. What makes good in-context examples for gpt-3? arXiv preprint arXiv:2101.06804, 2021.
- [11] Jerry Wei, Jason Wei, Yi Tay, Dustin Tran, Albert Webson, Yifeng Lu, Xinyun Chen, Hanxiao Liu, Da Huang, Denny Zhou, et al. Larger language models do in-context learning differently. arXiv preprint arXiv:2303.03846, 2023.
- [12] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *Journal of Machine Learning Research*, pages 1– 113, 2023.
- [13] Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. Finetuned language models are zero-shot learners. arXiv preprint arXiv:2109.01652, 2021.
- [14] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. Evaluating large language models trained on code. arXiv preprint arXiv:2107.03374, 2021.
- [15] Pantazis Deligiannis, Akash Lal, Nikita Mehrotra, and Aseem Rastogi. Fixing rust compilation errors using llms. arXiv preprint arXiv:2308.05177, 2023.
- [16] Aleksandra Eliseeva, Yaroslav Sokolov, Egor Bogomolov, Yaroslav Golubev, Danny Dig, and Timofey Bryksin. From commit message generation to history-aware commit message completion. arXiv preprint arXiv:2308.07655, 2023.
- [17] Zhaojian Yu, Xin Zhang, Ning Shang, Yangyu Huang, Can Xu, Yishu-jie Zhao, Wenxiang Hu, and Qiufeng Yin. Wavecoder: Widespread and versatile enhanced instruction tuning with refined data generation. arXiv preprint arXiv:2312.14187, 2023.
- [18] Saikat Chakraborty, Shuvendu K Lahiri, Sarah Fakhoury, Madanlal Musuvathi, Akash Lal, Aseem Rastogi, Aditya Senthilnathan, Rahul Sharma, and Nikhil Swamy. Ranking llm-generated loop invariants for program verification. arXiv preprint arXiv:2310.09342, 2023.
- [19] Chunqiu Steven Xia, Yuxiang Wei, and Lingming Zhang. Automated program repair in the era of large pre-trained language models. In Proceedings of the 45th International Conference on Software Engineering (ICSE 2023). Association for Computing Machinery, 2023.
- [20] Meng Chen, Hongyu Zhang, Chengcheng Wan, Zhao Wei, Yong Xu, Juhong Wang, and Xiaodong Gu. On the effectiveness of large language models in domain-specific code generation. arXiv preprint arXiv:2312.01639, 2023.
- [21] Max Schäfer, Sarah Nadi, Aryaz Eghbali, and Frank Tip. Adaptive test generation using a large language model. *arXiv preprint* arXiv:2302.06527, 2023.
- [22] Rosalia Tufano, Simone Masiero, Antonio Mastropaolo, Luca Pascarella, Denys Poshyvanyk, and Gabriele Bavota. Using pre-trained models to boost code review automation. In *Proceedings of ICSE*, page 2291–2302, 2022.
- [23] Zhiyu Li, Shuai Lu, Daya Guo, Nan Duan, Shailesh Jannu, Grant Jenks, Deep Majumder, Jared Green, Alexey Svyatkovskiy, Shengyu Fu, et al. Automating code review activities by large-scale pre-training. In *Proceedings of ESEC/FSE*, pages 1035–1047, 2022.
- [24] Chanathip Pornprasit, Chakkrit Tantithamthavorn, Patanamon Thongtanunam, and Chunyang Chen. D-ACT: Towards diff-aware code transfor-

- mation for code review under a time-wise evaluation. In *Proceedings of SANER*, pages 296–307, 2023.
- [25] Stephen Robertson, Hugo Zaragoza, et al. The probabilistic relevance framework: Bm25 and beyond. *Foundations and Trends*® *in Information Retrieval*, pages 333–389, 2009.
- [26] Jules White, Quchen Fu, Sam Hays, Michael Sandborn, Carlos Olea, Henry Gilbert, Ashraf Elnashar, Jesse Spencer-Smith, and Douglas C Schmidt. A prompt pattern catalog to enhance prompt engineering with chatgpt. arXiv preprint arXiv:2302.11382, 2023.
- [27] Michele Tufano, Jevgenija Pantiuchina, Cody Watson, Gabriele Bavota, and Denys Poshyvanyk. On learning meaningful code changes via neural machine translation. In *Proceedings of ICSE*, pages 25–36, 2019.
- [28] Shuo Ren, Daya Guo, Shuai Lu, Long Zhou, Shujie Liu, Duyu Tang, Neel Sundaresan, Ming Zhou, Ambrosio Blanco, and Shuai Ma. Codebleu: a method for automatic evaluation of code synthesis. arXiv preprint arXiv:2009.10297, 2020.
- [29] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Proceedings of NeurIPS*, pages 27730–27744, 2022.
- [30] Chengwei Qin, Aston Zhang, Zhuosheng Zhang, Jiaao Chen, Michihiro Yasunaga, and Diyi Yang. Is chatgpt a general-purpose natural language processing task solver? arXiv preprint arXiv:2302.06476, 2023.
- [31] Yingqi Qu, Yuchen Ding, Jing Liu, Kai Liu, Ruiyang Ren, Wayne Xin Zhao, Daxiang Dong, Hua Wu, and Haifeng Wang. Rocketqa: An optimized training approach to dense passage retrieval for open-domain question answering. *arXiv preprint arXiv:2010.08191*, 2020.
- [32] Yuanmeng Yan, Rumei Li, Sirui Wang, Hongzhi Zhang, Zan Daoguang, Fuzheng Zhang, Wei Wu, and Weiran Xu. Large-scale relation learning for question answering over knowledge bases with pre-trained language models. In *Proceedings of the 2021 conference on empirical methods in* natural language processing, pages 3653–3660, 2021.
- [33] Sebastian Ruder and Avirup Sil. Multi-domain multilingual question answering. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing: Tutorial Abstracts, pages 17–21, 2021.
- [34] Qian Ruan, Malte Ostendorff, and Georg Rehm. Histruct+: Improving extractive text summarization with hierarchical structure information. arXiv preprint arXiv:2203.09629, 2022.
- [35] Anshuman Mishra, Dhruvesh Patel, Aparna Vijayakumar, Xiang Lorraine Li, Pavan Kapanipathi, and Kartik Talamadupula. Looking beyond sentence-level natural language inference for question answering and text summarization. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1322–1336, 2021.
- [36] Giriprasad Sridhara, Sourav Mazumdar, et al. Chatgpt: A study on its utility for ubiquitous software engineering tasks. arXiv preprint arXiv:2305.16837, 2023.
- [37] Triet Huynh Minh Le, David Hin, Roland Croft, and M Ali Babar. Deepcva: Automated commit-level vulnerability assessment with deep multitask learning. In 2021 36th IEEE/ACM International Conference on Automated Software Engineering (ASE), pages 717–729, 2021.
- [38] Xiao Cheng, Haoyu Wang, Jiayi Hua, Guoai Xu, and Yulei Sui. Deepwukong: Statically detecting software vulnerabilities using deep graph neural network. ACM Transactions on Software Engineering and Methodology (TOSEM), 2021.
- [39] Saikat Chakraborty, Rahul Krishna, Yangruibo Ding, and Baishakhi Ray. Deep learning based vulnerability detection: Are we there yet. *IEEE Transactions on Software Engineering*, 2021.
- [40] Tae-Hwan Jung. Commitbert: Commit message generation using pretrained programming language model. arXiv preprint arXiv:2105.14242, 2021.
- [41] Wei Tao, Yanlin Wang, Ensheng Shi, Lun Du, Shi Han, Hongyu Zhang, Dongmei Zhang, and Wenqiang Zhang. A large-scale empirical study of commit message generation: models, datasets and evaluation. *Empirical Software Engineering*, page 198, 2022.
- [42] Lun Yiu Nie, Cuiyun Gao, Zhicong Zhong, Wai Lam, Yang Liu, and Zenglin Xu. Coregen: Contextualized code representation learning for commit message generation. *Neurocomputing*, pages 97–107, 2021.
- [43] Mingyang Geng, Shangwen Wang, Dezun Dong, Haotian Wang, Ge Li, Zhi Jin, Xiaoguang Mao, and Xiangke Liao. Large language models are few-shot summarizers: Multi-intent comment generation via in-context

- learning. 2024.
- [44] Toufique Ahmed and Premkumar Devanbu. Few-shot training llms for project-specific code-summarization. In Proceedings of the 37th IEEE/ACM International Conference on Automated Software Engineering, pages 1–5, 2022.
- [45] Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. ACM Computing Surveys, pages 1–35, 2023.
- [46] Jules White, Sam Hays, Quchen Fu, Jesse Spencer-Smith, and Douglas C Schmidt. Chatgpt prompt patterns for improving code quality, refactoring, requirements elicitation, and software design. arXiv preprint arXiv:2303.07839, 2023.
- [47] Alec Radford, Karthik Narasimhan, Tim Salimans, Ilya Sutskever, et al. Improving language understanding by generative pre-training. 2018.
- [48] Yue Wang, Weishi Wang, Shafiq Joty, and Steven CH Hoi. Codet5: Identifier-aware unified pre-trained encoder-decoder models for code understanding and generation. In *Proceedings of EMNLP*, pages 8696– 8708, 2021.
- [49] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *JMLR*, pages 1–67, 2020.
- [50] Rosalia Tufano, Luca Pascarella, Michele Tufano, Denys Poshyvanyk, and Gabriele Bavota. Towards automating code review activities. In Proceedings of ICSE, pages 163–174, 2021.
- [51] Sungmin Kang, Juyeon Yoon, and Shin Yoo. Large language models are few-shot testers: Exploring llm-based general bug reproduction. In 2023 IEEE/ACM 45th International Conference on Software Engineering (ICSE), pages 2312–2323. IEEE, 2023.
- [52] Shuzheng Gao, Xin-Cheng Wen, Cuiyun Gao, Wenxuan Wang, and Michael R Lyu. Constructing effective in-context demonstration for code intelligence tasks: An empirical study. In *Proceedings of ASE*, 2023.
- [53] Zhiqiang Yuan, Junwei Liu, Qiancheng Zi, Mingwei Liu, Xin Peng, and Yiling Lou. Evaluating instruction-tuned large language models on code comprehension and generation. arXiv preprint arXiv:2308.01240, 2023.
- [54] Qi Guo, Junming Cao, Xiaofei Xie, Shangqing Liu, Xiaohong Li, Bihuan Chen, and Xin Peng. Exploring the potential of chatgpt in automated code refinement: An empirical study. arXiv preprint arXiv:2309.08221, 2023.
- [55] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: A method for automatic evaluation of machine translation. In *Proceedings* of ACL, pages 311–318, 2002.