

# AdvFusion: Adapter-based Knowledge Transfer for Code Summarization on Code Language Models

1<sup>st</sup> Author Name

University

Country

Email Address

2<sup>nd</sup> Author Name

University

Country

Email Address

3<sup>rd</sup> Author Name

University

Country

Email Address

4<sup>th</sup> Author Name

University

Country

Email Address

**Abstract**—Programming languages can benefit from one another through utilizing a pre-trained model for software engineering tasks such as code summarization and method name prediction. Such benefits were shown in empirical studies on multilingual fine-tuning of Code Language Models (Code-LM). Though these studies used full fine-tuning, Parameter Efficient Fine-Tuning (PEFT) has shown to be a promising alternative approach for many software engineering tasks in other studies. However, there is limited research on studying the knowledge transfer among languages through PEFT architectures that utilize multiple languages. AdapterFusion is one such architecture that enhances the performance of a target task in a specific language, by learning from similar latent information from other languages. However, our empirical studies show that AdapterFusion primarily learns the same language of the target task, even though there are multiple languages involved.

We therefore, propose AdvFusion, an innovative PEFT-based approach that can effectively learn useful information from other languages. AdvFusion first learns the knowledge of other programming languages, before learning from the language corresponding to the target task and adapting the previously learned knowledge to it. We choose two commonly used downstream tasks, code summarization and method name prediction, to evaluate our proposed approach. Our experiments show that AdvFusion outperforms AdapterFusion by up to 1.7-point increase on the benchmark datasets, and exceeds LoRA by 1.99, 1.26, and 2.16 for Ruby, JavaScript, and Go, respectively. We open source our scripts for replication purposes<sup>1</sup>.

**Index Terms**—Parameter Efficient Fine-tuning, Adapter Fine-tuning, Code-Language Models, Code Summarization, Method Name Prediction

## I. INTRODUCTION

Language Models (LMs), pre-trained on extensive datasets, have gained popularity in recent years. In Software Engineering (SE), domain-specific LMs, known as Code-LMs, trained on code, excel in various tasks such as code summarization, bug prediction, and method name prediction [1]–[8]. Code-LMs are trained on code and/or its comments and fine-tuned on specific tasks. Multiple studies explore various approaches to optimally fine-tune code-LMs, including considerations in using mono-lingual or multi-lingual datasets for fine-tuning [9], and using similar programming language datasets for target languages [10]. Others focus on enhancing results for low-resource languages [2], [10], [11] and using alternative fine-tuning methods, such as Parameter Efficient Fine-Tuning

(PEFT), to address computational resource constraints [6]–[8], [12]–[16]. PEFT methods are introduced as alternatives to fine-tuning all parameters of code-LMs (i.e., full fine-tuning) as they require less number of parameters and computational costs [17].

Previous research has shown that PEFT methods are effective for the transferability of natural language models to programming languages tasks with reduced training costs [12]. New PEFT architectures were also shown to be effective in imposing syntactical information to code-LMs and improving their results compared to fully fine-tuning them [18]. Other works include empirical studies of PEFT in different settings, including in a multilingual setting, where a dataset of multiple programming languages is used to fine-tune the code-LM for downstream tasks [19], and evaluating the benefits of PEFT methods for SE tasks [6]–[8], [20].

Though multiple studies have been conducted on using code-LMs in software engineering and on analysing the benefits of PEFT in a multilingual setting, there is a gap in bridging the above-mentioned directions: transferring the knowledge from code-LMs of multiple programming languages to a target programming language task using PEFT.

Among the PEFT methods, a specific architecture known as *AdapterFusion* [14] learns to enhance the performance of a target task of a specific language, by leveraging similar latent information from other languages. AdapterFusion is based on *Adapter*, a light-weight module inserted between the Transformer layers [17]. However, when we applied AdapterFusion in our experiments, we found that the model is learning mainly from the same language of the target task, rather than leveraging knowledge from other programming languages. As a result, we propose **Adversarial Fusion Adapter (AdvFusion)**, a new PEFT architecture that enforces AdapterFusion to first learn from the other programming languages before the target programming language. In this way, AdvFusion enhances the knowledge transfer among programming languages. The word ‘Adversarial’ was chosen for AdvFusion because we train the model in an adversarial manner, diverging from the conventional approach of creating adversarial samples.

In evaluating AdvFusion, we first experiment the effect of inserting mono-lingual PEFT methods trained on a specific task. We then use AdapterFusion to assess the existing PEFT architecture in learning from other programming languages.

<sup>1</sup><https://anonymous.4open.science/r/AdvFusion-5841/README.md>

We compared our results against both mono-lingual and multi-lingual PEFT methods on Code-LLMs.

We choose two target tasks in our experiments, code summarization and method name prediction because they have been shown to enhance program comprehension and positively impact programmers’ productivity [3], and they are widely studied in the literature [1], [2], [9], [19], [21].

It is worth noting that we aim to use the knowledge transfer among programming languages through AdvFusion on smaller Code-LLMs such as CodeT5+ [22], CodeBERT [5] and GraphCoderBERT [4], rather than Large Language Models trained on Code (Code-LLMs), such as CodeLlama [23] and StarCoder [24] with billions of parameters. Recent studies by [25] on how code-LLMs and code-LLMs understand code reveals that fine-tuning code-LLMs on a target task could be more effective compared to code-LLMs [25]. This is further supported by [26] for another SE task. Given these findings, we aim to exploit the capabilities of code-LLMs and propose a speedier fine-tuning approach to improve their performance.

Our evaluation on six programming languages from the CodeSearchNet dataset demonstrates that AdvFusion significantly enhances the performance of multilingual PEFT approaches in code summarization, showing improvements of up to 10% across various models. Additionally, AdvFusion boosts method name prediction performance, achieving up to a 9% increase in F1-score compared to AdapterFusion. Furthermore, AdvFusion outperforms LoRA, a widely recognized PEFT technique, by up to 12% in code summarization and as much as 32% in method name prediction.

PEFT approaches are attractive choices to fine-tune language models for downstream tasks with less number of parameters both in NLP and SE [13], [14], [18], [19]. The importance of PEFT is more discernible when the computational resources are limited. Additionally, it has been shown that language models do not perform well on low-resource languages (i.e., languages with less training data) [4], [5]. We observed that our proposed method also enhances the performance of low-resource languages in some cases in our experiments.

Our contributions are as follows.

- Empirically study the capabilities of AdapterFusions for multilingual fine-tuning, in the context of code summarization and method name prediction.
- Propose an effective new PEFT architecture, AdvFusion, for fostering knowledge transfer from multiple programming languages to a target programming language task in the multi-lingual setting.

The rest of the paper is organized as follows. In Section II, we provide an overview of necessary background information and then discuss about the effectiveness of the current PEFT method for multi-lingual training in section III. We introduce our novel PEFT architecture, AdvFusion, in Section IV. In Section V we provide the research questions and experimental setup. Results are explained in Section VI and they are further discussed in Section VII. Sections VIII and IX are dedicated to

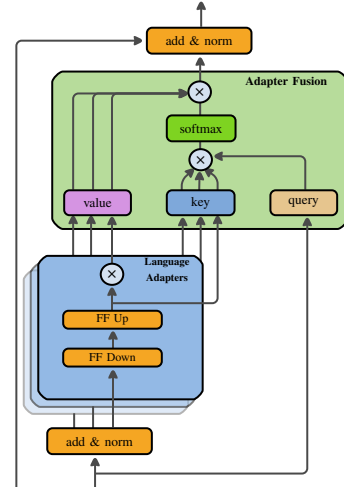


Fig. 1: Internal structure of AdapterFusion.

the related works and threats to validity. Finally, we conclude the paper in Section X.

## II. BACKGROUND

### A. Adapters

We used various adapter types in our approach: task adapters, language adapters, and AdapterFusions. Adapters are lightweight modules added to a language model’s internal structure, providing an efficient alternative to traditional fine-tuning for new tasks and preventing catastrophic forgetting. Adapters require less computational time and resources than fine-tuning.

Let  $\Theta$  represent all weights of a pre-trained model. When an adapter  $i$  is added, a new set of weights  $\theta_i$  is created. During training,  $\Theta$  remains frozen, and only  $\theta_i$  is trained for the downstream task.

1) *Task Adapters*: The aim of a task adapter is to learn a task-specific functionality by training its weights on a target task dataset [13]. Task adapters consist of a simple down- and up- projection combined with residual connections. Task adapter  $TA_l$  at layer  $l$  consists of a down-projection  $D \in R^{h \times d}$  where  $h$  is the hidden size of the Transformer and  $d$  is the dimension of the adapter. The down-sampled representations are then fed to a ReLU activation followed by an up-projection transformation  $U \in R^{d \times h}$  at each layer. This is shown in Equation 1:

$$TaskAdapter_l(h_l, r_l) = U_l(ReLU(D_l(h_l))) + r_l \quad (1)$$

In RQ1, we used task adapters for code summarization, trained on labeled data.  $h_l$  and  $r_l$  denote hidden state and residuals at layer  $l$ .

2) *Language Adapters*: Language adapters learn language-specific features by training their weights on an abstract objective function such as MLM [13]. The language adapter  $LA_l$  at layer  $l$  has the same architecture as a task adapter. The

internal structure of a language adapter consists of a down-projection  $D \in R^{h \times d}$  with a ReLU activation, followed by an up-projection  $U \in R^{d \times h}$ , as shown in Equation 2:

$$\text{LanguageAdapter}_l(h_l, r_l) = U_l(\text{ReLU}(D_l(h_l))) + r_l \quad (2)$$

where  $h_l$  and  $r_l$  are defined similar to task adapters. Language adapters differ from task adapters in that they are trained on unlabeled data using Masked Language Modeling (MLM), focusing on learning specific language embeddings. These embeddings can then be employed as input for task adapters or combined with AdapterFusion for extracting latent knowledge for downstream tasks.

3) *AdapterFusion*: Language adapters are introduced to extract language specific embeddings from the internal structure of an LM based on an abstract objective function such as MLM to learn the general representations of a language. AdapterFusion aims to extract and compose the latent knowledge from multiple language adapters for a downstream task such as code summarization. For example, given a set of  $N$  language adapters, the output of adapterFusion is a weighted sum of outputs from the language adapters, while the weights of the LMs weights ( $\Theta$ ) and the language adapter ( $\theta_1, \dots, \theta_N$ ) are fixed. This is shown in Equation 3:

$$\Phi = \text{argmin } L(D; \Theta, \theta_1, \dots, \theta_N) \quad (3)$$

where  $\Phi$  consists of the  $Key_l$ ,  $Value_l$  and  $Query_l$  metrics at each layer  $l$ . At each Transformer block, the output of the feed-forward sub-layer is taken to be the  $Query$ , and the output of each language adapter is used for both  $Key$  and  $Value$  vectors. Fig. 1 shows the internal structure of AdapterFusion.

### III. EFFECTIVENESS OF ADAPTERFUSION

Previous research [9] shows that fully fine-tuning a Code-LM on a multilingual dataset improves the performance of the models for code summarization task. Additionally, it is shown that during the fine-tuning phase, if we encourage the weights to stay closer to the initial weights of the LMs, we can avoid catastrophic forgetting and stabilize the fine-tuning process [27]. Therefore, we hypothesize that using a PEFT architecture that is designed to learn from other tasks/languages, i.e., AdapterFusion, will improve the performance compared to full fine-tuning a Code-LM on multilingual data. To analyze the effectiveness of AdapterFusion in a multilingual setting, we choose three Code-LMs, CodeT5p+(220M) [22] denoted as CodeT5p for the rest of the paper, CodeBERT [5] and GraphCodeBERT [4].

We first train language adapters, one for each of the six languages from the CodeSearchNet dataset. Then, we stack the trained language adapters and fine-tune AdapterFusion for two tasks, code summarization and method name prediction, fixing the parameters of the Code-LMs and the language adapters. We denote these models as CodeT5p+AdapterFusion, CodeBERT+AdapterFusion and GraphCodeBERT+AdapterFusion.

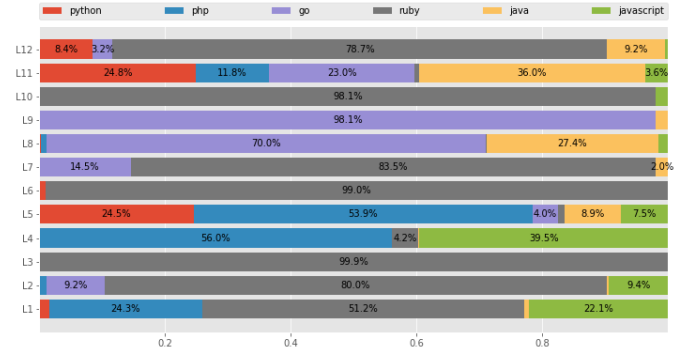


Fig. 2: The attention contribution from each programming language at each layer when we feed the Ruby test dataset to the fine-tuned AdapterFusion model.

Additionally, we performed experiments in a monolingual setting to evaluate the effectiveness of multilingual versus monolingual PEFT approaches. In this setting, the fine-tuning dataset consists of code summarization or method name prediction tasks for a single programming language. For these experiments, we fine-tuned the selected code language models (Code-LMs) using two types of adapters: task adapters and LoRA adapters. To do this, the base weights of the code models were kept frozen, while we integrated the corresponding adapters into the models for task-specific fine-tuning. We refer to these modified models as CodeT5p+TaskAdapter, CodeBERT+TaskAdapter, and GraphCodeBERT+TaskAdapter when using task adapters, and CodeT5p+LoRA, CodeBERT+LoRA, and GraphCodeBERT+LoRA when using LoRA adapters.

The obtained scores for code summarization are shown in Table III. There are several observations here. First, the use of TaskAdapters and LoRA in conjunction with Code-LMs leads to improved performance compared to full fine-tuning for both CodeBERT and GraphCodeBERT on three specific languages: Ruby, JavaScript, and Go. Additionally, the results achieved using TaskAdapters and LoRA are comparable to those obtained by other models in these languages.

Notably, we employed only 0.89 million of trainable parameters for fine-tuning with task adapters, significantly fewer than the fully fine-tuned CodeBERT and GraphCodeBERT models with 110 million parameters. This result is aligned with previous research [28].

Second, we noticed that AdapterFusion helps improve the results of mono-lingual adapters, i.e., Code-LM+TaskAdapters for CodeBERT, and has similar scores for GraphCodeBERT and CodeT5p.

Table IV presents the results for method name prediction. For CodeBERT and GraphCodeBERT, AdapterFusion demonstrates superior performance compared to TaskAdapters and LoRA. However, in the case of CodeT5p, the impact of the multilingual setting is less pronounced. We hypothesize that this is because CodeT5p, being a larger model, can effectively leverage the CodeSearchNet dataset during pre-training, re-

ducing the need for further adaptation in multilingual settings.

Here, we aim to uncover the underlying mechanics of applying AdapterFusion in a multilingual PEFT setting, providing insight into its inner workings and effects on model performance. Figure 2 presents the attention contribution of each programming language when AdapterFusion is used for code summarization in Ruby. The x-axis shows the attention score and the y-axis shows the contribution of each language at each layer in percentage. The color bars show the contributions from each of the six programming languages. In most layers, a high percentage of attention (more than 80%) is towards Ruby (the gray bar). This shows that AdapterFusion tends to pay more attention to the language adapter that corresponds to the same language of the target task. This figure also suggested that AdapterFusion could benefit from an architectural change to achieve its goal, which is to learn from other programming languages. In the next section, we detail our proposed architecture, AdvFusion to achieve this goal.

#### IV. ADVERSARIAL FUSION ADAPTER

In this section, we describe the architecture of our approach, AdvFusion, before proposing a learning algorithm for it.

##### A. Architecture

AdapterFusion can leverage the language adapter corresponding to the language of the current input better [14], i.e., it pays more attention to the language adapter of the target task. This is mainly due to its internal attention mechanism. This mechanism prevents the effective utilization of the other language adapters, thus rendering them redundant. In light of this, we propose a new architecture, AdvFusion, that requires AdapterFusion to learn more from the other language adapters that are trained using a different language from the target task. Our approach consists of two training phases, Adversarial training phase and Fine-tuning phase:

- 1) Adversarial training phase (see Fig. 3): In this phase, (i) the weights of the language adapter that corresponds to the language of the target task are set to zero, while (ii) the weights of the code-LM and the other language adapters are fixed. Then, (iii) AdvFusion is trained on the entire dataset. This phase allows AdvFusion to learn from the other language adapters.
- 2) Fine-tuning phase (see Fig. 4): In this phase, AdvFusion would have learnt from the other language adapters in the earlier phase. However, we still want AdvFusion to learn from the language adapter that corresponds to the language of the target task. Thus, (i) we restore the trained weights of the language adapter that corresponds to the language of the target task, while still (ii) fixing the weights of the code-LM and all language adapters. Then, (iii) the weights of AdvFusion are fine-tuned.

##### B. Learning Algorithm

In this section, we formalize the learning procedure of AdvFusions. Let  $\Theta$  and  $\theta_i$  denote the parameters of the code-LM and each language adapter, *language<sub>i</sub>*, respectively. We

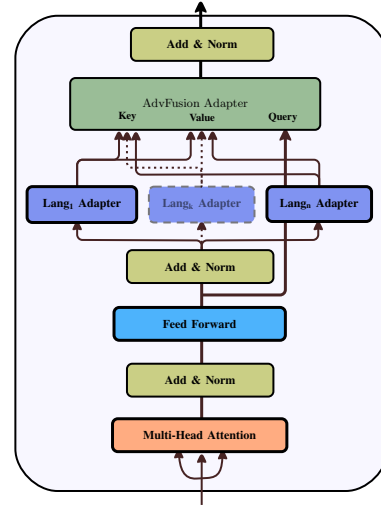


Fig. 3: The adversarial training phase of AdvFusion.

introduce the  $\Psi$  parameters to learn an embedding space from  $N$  language adapters for a downstream task. For the adversarial training phase, we formalize it as follows:

$$\Psi \leftarrow \underset{\Psi}{\operatorname{argmin}} \sum_{m=1}^N L(D_m; \Theta, \theta_1, \dots, \theta_{m-1}, \theta_{m+1}, \dots, \theta_N, \Psi) \quad (4)$$

where  $L$  is the loss function of the downstream task, and  $D_m$  denotes the *language<sub>m</sub>* dataset. In this step, AdvFusion learns to compose the embeddings of  $N-1$  language adapters at each training step (recall that we are only interested in learning from the other language adapters that differ from the language of the target task in the adversarial training phase, thus we are only learning from  $N-1$  language adapters).

In the second phase, we employ all the language adapters to train the  $\Psi$  parameters as follow:

$$\Psi \leftarrow \underset{\Psi}{\operatorname{argmin}} \sum_{m=1}^N L(D_m; \Theta, \theta_1, \dots, \theta_N, \Psi) \quad (5)$$

As illustrated in Fig. 3,  $\Psi$  consists of the *Key*, *Value* and *Query* parameters, denoted by  $K_l$ ,  $V_l$  and  $Q_l$  at the Transformer layer  $l$ , respectively.

Let  $h_l$  denote the output of the feed-forward sub-component at the Transformer layer  $l$ . This is an input to AdvFusion. The output of the language adapter  $i$  at the Transformer layer  $l$ , denoted as  $z_{l,i}$ , is the input for both the *Key* and *Value* transformations at the Transformer layer  $l$ . We compute the output of AdvFusion, denoted by  $O_l$ , as follows:

$$\begin{aligned} S_l &= \operatorname{softmax}(h_l^T Q_l \otimes z_{l,n}^T K_l) \\ z'_{l,n} &= z_{l,n}^T V_l \\ Z'_l &= [z'_{l,0}, \dots, z'_{l,N}] \\ O_l &= S_l^T Z'_l \end{aligned} \quad (6)$$

Given the embeddings of each language adapter ( $z_n$ ), AdvFusion learns a weighted mixer of the available trained

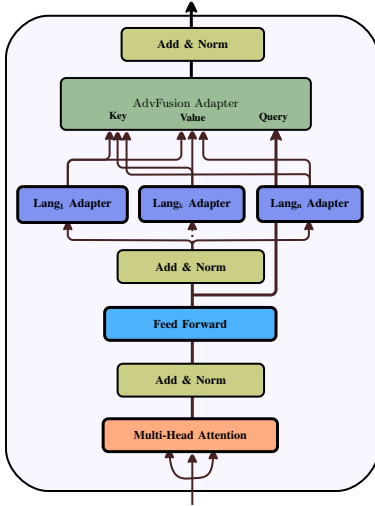


Fig. 4: The fine-tuning phase of AdvFusion.

language adapters. In equation 6,  $\otimes$  represents the dot product and  $n$  refer to two different things in each of the phases in AdvFusion. In the adversarial training phase (first phase),  $n \in \{1, \dots, m-1, m+1, \dots, N\}$  while in the fine-tuning phase (second phase),  $n \in \{1, \dots, N\}$ .

## V. EXPERIMENT SETUP

In this section, we discuss the research questions and the details of our study design and experiment setup.

### A. Research Questions

In this study, we conduct experiments to answer the following research questions:

**RQ1:** Does using AdvFusion lead to a performance improvement in multilingual fine-tuning?

In this RQ, our goal is to evaluate the effectiveness of multilingual fine-tuning a language model designed for code, utilizing our innovative approach, AdvFusion. The primary objective of AdvFusion is to emphasize on the knowledge transfer across various programming languages, ultimately improving the overall performance and adaptability of the model. AdvFusion operates by selectively extracting, exploiting, and aggregating the latent knowledge acquired from different programming languages. Within the scope of this RQ, we aim to assess the extent to which the programming languages can benefit from the knowledge derived of others. As this learning is enforced in AdvFusion, it is compared against AdapterFusion.

**RQ2:** How much attention is placed on the target language from the other (non-target) languages in AdvFusion?

Constructing good-quality datasets for a target programming languages is a time consuming and challenging task. Previous studies have attempted to take advantage of other (non-target) programming languages for a target programming language through a multilingual training dataset [9], [10]. As the AdvFusion architecture enables learning from other languages in an initial stage, we are interested to see the amount of

contributed attention from other languages. In this RQ, we use attention analysis to evaluate how much we can learn from other programming languages for a target language. More specifically, we calculate the participation of each language at every transformer block of the model by measuring the percentage of attention we get from each language adapter for each sample over a target language dataset.

### B. Backbone Models

We have selected CodeT5+(220M) [22], CodeBERT [5] and GraphCodeBERT [4] as our baseline models for several reasons. CodeT5+220M is introduced recently and considered as an improved version of CodeT5 [29]. The other models have been extensively researched in the field of software engineering [9], [18], [19], [30], [31]. Additionally, these models are studied for multilingual fine-tuning for these two tasks and therefore serve as a basis in our comparisons [9].

Please note that, recent studies by [25] on how code language models (code-LMs) and code large language models understand code reveal that fine-tuning smaller models on a target task could be more effective as compared to code-LLMs with billions of parameters. This finding is further supported by [26] for another software engineering task. Given these findings, we aim to exploit the capabilities of code-LMs and propose a speedier fine-tuning approach to improve their performance.

**CodeT5+** is an advanced code-LM designed by [22] to overcome limitations in existing code models, which often rely on rigid encoder-only or decoder-only architectures. It introduces a flexible, modular approach, allowing customization for various code-related tasks. CodeT5+ achieves superior performance compared to other code-LMs of a similar size by incorporating a combination of pre-training techniques, including span denoising and contrastive learning.

**CodeBERT**, as introduced by [5], is a bimodal pretrained model designed for both natural language and programming language understanding. Its architecture is based on Transformers. CodeBERT employs two pre-training objectives, namely Masked Language Modeling and Replaced Token Detection. These objectives are specifically chosen to enhance its capabilities in supporting tasks such as code search and code documentation generation.

**GraphCodeBERT**, introduced by [4], is a pioneering pre-trained model designed to enhance code comprehension tasks such as code summarization. GraphCodeBERT utilizes semantic-level information from code, specifically focusing on aspects like data flow. This pre-training approach employs a 12-layer transformer-based architecture. It is pre-trained on Masks Language Modeling, Edge Prediction and Node Alignment objective functions.

### C. Tasks

1) *Code Summarization:* Given a code snippet, the task of code summarization is to describe its functionality. It enhances code readability, aids in program comprehension, and facilitates easier maintenance and documentation. By providing



summaries, developers can quickly understand the purpose and functionality of a piece of code without delving into its implementation details [32]. Code summarization is chosen as it is a widely studied task and the effects of multilingual fine-tuning for this task is investigated in previous research [9], [19].

**Evaluation metric** We evaluate the code summarization task using smooth-BLEU-4 [33], which is a widely used metric in natural language generation tasks and many software engineering studies [4], [5], [19], [29], [34]. BLEU is a precision-based metric that measures the n-gram geometric precision between the generated summary (i.e., n-gram hit) and the ground truth summary (i.e., total n-gram count) [33].

2) *Method Name Prediction*: The objective of the method name prediction task is to generate the most fitting method name that describes the purpose and functionality of the method’s code. This task is chosen because naming methods accurately is crucial for code readability, maintainability, and understanding.

**Evaluation metric** We report precision, recall and F1-score for the generated method names. F1 Score is the weighted average of Precision and Recall:  $F1 = \frac{2 \cdot (P \cdot R)}{P + R}$ . Where P and R stand for Precision and Recall, respectively.

Precision is computed as  $P = \frac{TP}{TP + FP}$ , whereas Recall is calculated as  $R = \frac{TP}{TP + FN}$ . P is calculated as the length of the intersection of ground truth tokens and generated output tokens (i.e., TP) divided by the length of output tokens (i.e., TP + FP). Similarly, R represents the recall, calculated as the length of the intersection of ground truth tokens and generated output tokens (i.e., TP) divided by the number of ground truth tokens (i.e., TP + FN).

#### D. Baselines

AdvFusion in a Code-LM should be compared against the same Code-LM+AdapterFusion. For example, we should compare CodeBERT+AdvFusion with CodeBERT+AdapterFusion.

To show the effectiveness of the base PEFT architecture we used, we also provide the results for mono-lingual fine-tuning, including Code-LMs+TaskAdapters and Code-LMs+LoRA [15]. Note that we perform experiments on LoRA [15] as it is a widely used PEFT method. This enables us to compare its performance against other approaches and AdvFusion.

#### E. Experiments Design

Our study delves into the code summarization and method name prediction tasks, aiming to gather diverse programming language knowledge.

To train AdvFusion, in the first phase, we (1) fix the weights of the language adapter, (2) temporarily set the weights of the language adapter corresponding to the current input (i.e., the language of the target task) to zero, and (3) train the weights of AdvFusion on our target task. In the second phase, we restore the weights of the language adapter corresponding to the input and allow AdvFusion to learn from the language adapter that corresponds to the language of the current input.

For *RQ2*, we evaluate the contribution of each programming language for a target programming language. Here, we choose Ruby, as our experiments in Section III shows that it could benefit from other programming languages. Ruby is also used as a low resource language in previous studies [10] and it has been shown that it can benefit from other languages.

We compute the contributions by feeding the Ruby test dataset into CodeBERT+AdapterFusion. Then, we aggregate the attention scores from each language adapter in each layer, normalize them (i.e., min-max normalization), and obtain the percentage of each language’s contribution. We repeat these steps for CodeBERT+AdvFusion to compare its ability with AdapterFusion in extracting knowledge from other programming languages for Ruby. You can find the other language contributions on the repository page<sup>2</sup>. All experiments are conducted on an Nvidia Tesla V100 32GB GPU.

#### F. Training Details

As Pfeiffer et al. has performed an extensive hyperparameter search over adapters, we use their reported optimal settings in our adapters’ hyperparameters [14].

We use the CodeSearchNet datasets [35] for training the language adapters. It consists of datasets from 6 programming languages and the size of each language is shown in Table I. We train language adapters using Mask Language Modelling.

We fine-tune AdapterFusion and AdvFusion adapters on the CodeSearchNet datasets using the next token prediction objective function for code summarization. For the method name prediction task, we exclusively utilize the code portion of the CodeSearchNet datasets. We then mask the method names and let each approach to suggest new method names using the next token generation objective function.

Language	# of Bimodal Data	Language	# of Bimodal Data
Ruby	24,927	Python	251,820
JavaScript	58,025	Java	164,923
Go	167,288	PHP	241,241

TABLE I: Dataset statistics. [35]

## VI. RESULTS

In this section, we present the results of our experiments, including the time reduction when AdvFusion is used.

#### A. *RQ1: Performance of Multilingual PEFT with AdvFusion*

In this RQ, we evaluate how much improvement we could gain by using other programming languages, therefore, transferring knowledge in the multilingual parameter efficient fine-tuning of Code-LMs.

In Table III, we present the BLEU scores for both multilingual and monolingual PEFT approaches applied to Code-LMs. The multilingual approaches include Code-LM with AdvFusion and AdapterFusion, while the monolingual approaches involve Code-LM with TaskAdapter and LoRA. Although the

<sup>2</sup><https://anonymous.4open.science/r/AdvFusion-5841/README.md>

Language	CodeBERT	CodeBERT+AdvFusion	Time reduction
Ruby	492	328	-33% ↓
JavaScript	493	344	-30% ↓
Go	511	336	-34% ↓
Python	493	323	-34% ↓
Java	494	341	-31% ↓
PHP	506	338	-33% ↓

TABLE II: AdvFusion time efficiency for code summarization. Numbers represent training time in minutes, with the last column showing percentage improvement. Times reflect training for 20,000 training steps.

base Code-LMs are the same, the key difference lies in the fine-tuning strategies used.

With CodeBERT+AdvFusion, we observe improvements of 8%, 6%, 7%, and 5% in BLEU scores for Ruby, JavaScript, Go, and Java, respectively. Similarly, with GraphCodeBERT+AdvFusion, we see gains of 6%, 10%, 8%, and 4% for the same languages. However, for Python and PHP, CodeBERT+TaskAdapter and GraphCodeBERT+LoRA show higher performance. We attribute this to the larger training data available for Python and PHP compared to Ruby and JavaScript, which have fewer samples. The smaller datasets for Ruby and JavaScript suggest that these languages still benefit from additional knowledge transfer.

We also compare the performance of AdvFusion with the state-of-the-art PEFT method, LoRA. In five of the programming languages evaluated (excluding Python), AdvFusion consistently outperforms LoRA. The performance gains are especially pronounced for CodeBERT and GraphCodeBERT, while the improvement for CodeT5p is less substantial. To better understand this discrepancy, we manually analyzed the outputs of CodeT5p+AdapterFusion and CodeT5p+AdvFusion against the ground truth targets, as shown in Table V. Although the overall improvement for CodeT5p is modest, our analysis reveals that AdvFusion tends to capture finer details more effectively.

In terms of parameter efficiency, both AdapterFusion and AdvFusion are more efficient than fully fine-tuning CodeBERT. As shown in Table II, the average time for fine-tuning all the weights of CodeBERT was approximately 8 hours. In contrast, fine-tuning CodeBERT with AdvFusion took around 5.5 hours, representing a reduction of about 44% in training time compared to full fine-tuning of the entire model.

We perform method name prediction on our baseline CodeLMs. The results are shown in Table IV. For this task, we observe that both AdapterFusion and AdvFusion have a larger impact on the results when they are added to GraphCodeBERT. This improvement is significant for all languages. For both models, AdvFusion slightly improves the results of AdapterFusion or achieves the same scores. We hypothesize the variation could stem from the initial disparity in inputs and training methods between CodeBERT and GraphCodeBERT. GraphCodeBERT, utilizing dataflow graphs as input, gains a deeper understanding of the internal connections within code elements. This enhanced comprehension of the relationships among the programming languages enables GraphCodeBERT

to suggest more effective method names by leveraging the knowledge from other programming languages for the language of the target task, when AdvFusion is used.

**When *AdvFusion* is used for fine-tuning Code-LMs, we can achieve a better or on-par results compared to other PEFT methods. The improvement is observed more for the the three programming languages Ruby, JavaScript, and Go for code summarization. As AdvFusion is a PEFT method, the training time is reduced and approximately 80% less parameters are trained compared to full fine-tuning the Code-LMs.**

#### B. RQ2: Languages' Contribution for a target Programming Language

We assess the contribution of each language adapter across all programming languages for code summarization, comparing AdvFusion with AdapterFusion. Due to space constraints, we present only the results for Ruby, as the behavior of other languages follows a similar trend. Figures illustrating the contributions of the other languages are available in the supplementary materials.

We extract the attention at AdvFusion and AdapterFusion when we fine-tune CodeLMs+AdvFusion and CodeLMs+AdapterFusion, respectively (separate experiments). Fig. 2 demonstrates the contribution of each language at each layer in CodeBERT+AdapterFusion when the Ruby test dataset is fed to the fine-tuned model. As discussed previously, it is noted that in most layers, a high percentage of attention (more than 80%) is towards Ruby (the gray bar), rather than attending to other languages. In other words, not much is learned from other programming languages.

**Programming languages could benefit from the other resourceful languages differently in different layers. Higher resource languages do not necessarily contribute more to the low-resource language, such as Ruby.**

Fig. 5 shows the contribution of each language in CodeBERT + AdvFusion when the Ruby test dataset is fed to the fine-tuned model. The y-axis is the layer number in CodeBERT, and the x-axis shows the percentage of contribution of each language. Here, AdvFusion pays more attention to other programming languages. For instance, Ruby has the following learning: it learns more from Go in the second layer (i.e., 52.9% of attention are grabbed from Go adapter), it learns more from Python than Ruby in the forth layer (i.e., 56.2%), and it learns more from JavaScript in layer seven. Even in the higher layers, learning from other languages is continued and the attention is distributed to other languages, and not only focused on Ruby. More interestingly, PHP is the most resourceful language in the dataset, but its contribution for Ruby is less than other languages. This suggests that there is

Models	Ruby	JavaScript	Go	Python	Java	PHP
CodeT5p+AdvFusion	14.70	<b>14.96</b>	18.25	<b>18.98</b>	<b>18.78</b>	<b>23.87</b>
CodeT5p+AdapterFusion	<b>14.79</b>	14.82	18.30	18.94	18.71	23.80
CodeT5p+TaskAdapter	13.99	14.31	<b>18.34</b>	18.91	18.68	23.71
CodeT5p+LoRA	13.56	14.25	18.08	18.88	18.67	23.47
CodeT5p (Full Fine-Tuned)	14.55	15.16	19.00	19.77	19.60	25.13
GraphCodeBERT+AdvFusion	<b>16.47</b>	<b>15.89</b>	<b>19.96</b>	18.49	<b>18.97</b>	<b>24.83</b>
GraphCodeBERT+AdapterFusion	15.57	14.49	18.21	17.86	18.21	23.54
GraphCodeBERT+TaskAdapter	14.39	14.53	18.47	17.88	17.29	23.36
GraphCodeBERT+LoRA	14.48	14.63	17.8	<b>18.50</b>	17.16	24.13
GraphCodeBERT (Full Fine-Tuned)	12.62	14.79	18.40	18.02	19.22	25.45
CodeBERT+AdvFusion	<b>16.53</b>	<b>16.80</b>	<b>19.69</b>	18.28	<b>19.94</b>	25.20
CodeBERT+AdapterFusion	15.38	15.88	18.31	18.40	19.04	25.17
CodeBERT+TaskAdapter	14.12	15.67	18.51	<b>18.47</b>	18.99	<b>25.55</b>
CodeBERT+LoRA	12.27	13.67	19.01	17.07	16.58	23.08
CodeBERT(Full Fine-Tuned)	12.16	14.90	18.07	19.06	17.65	25.16

TABLE III: Smooth BLEU-4 scores on code summarization. When AdvFusion is combined with Code-LMs, we saw an improved performance in majority of the datasets.

Model	Ruby			Javascript			Go			Python			Java			PHP		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
CodeT5p + AdvFusion	<b>0.55</b>	<b>0.55</b>	<b>0.55</b>	<b>0.59</b>	<b>0.56</b>	<b>0.58</b>	<b>0.58</b>	<b>0.56</b>	<b>0.57</b>	0.61	0.61	0.61	<b>0.61</b>	0.57	<b>0.59</b>	<b>0.49</b>	0.46	<b>0.48</b>
CodeT5p + AdapterFusion	0.54	0.54	0.54	0.57	0.55	0.56	0.55	0.53	0.54	0.60	0.59	0.60	0.59	0.56	0.57	0.47	0.44	0.46
CodeT5p + TaskAdapter	0.53	0.54	0.54	0.54	0.57	0.55	0.55	0.57	0.56	0.61	0.61	0.61	0.60	0.57	0.59	0.48	0.46	0.47
CodeT5p+LoRA	0.53	0.52	0.53	0.53	0.56	0.55	0.54	0.56	0.55	<b>0.61</b>	<b>0.61</b>	<b>0.61</b>	0.57	<b>0.59</b>	0.58	0.48	0.45	0.46
CodeBERT + AdvFusion	<b>0.39</b>	0.32	<b>0.35</b>	0.19	0.14	0.16	<b>0.46</b>	<b>0.46</b>	<b>0.45</b>	<b>0.47</b>	<b>0.45</b>	<b>0.46</b>	0.43	0.34	0.37	<b>0.45</b>	<b>0.43</b>	<b>0.44</b>
CodeBERT + AdapterFusion	0.38	0.30	0.32	0.19	0.14	0.16	0.45	0.40	0.41	0.44	0.34	0.37	0.43	0.34	0.37	0.45	0.38	0.40
CodeBERT + TaskAdapter	0.35	0.30	0.30	0.19	0.14	0.16	0.45	0.40	0.41	0.44	0.34	0.37	0.43	0.34	0.37	0.45	0.38	0.40
CodeBERT+LoRA	0.36	<b>0.33</b>	0.34	<b>0.21</b>	<b>0.16</b>	<b>0.18</b>	0.45	0.42	0.43	0.43	0.45	0.44	0.42	<b>0.40</b>	<b>0.41</b>	0.41	0.44	0.43
<b>Graph CodeBERT + AdvFusion</b>	<b>0.42</b>	<b>0.32</b>	<b>0.36</b>	<b>0.58</b>	<b>0.58</b>	<b>0.58</b>	<b>0.51</b>	<b>0.51</b>	<b>0.51</b>	0.49	0.40	0.42	<b>0.52</b>	<b>0.50</b>	<b>0.51</b>	<b>0.54</b>	<b>0.53</b>	<b>0.54</b>
<b>Graph CodeBERT + AdapterFusion</b>	0.40	0.30	0.35	0.57	0.57	0.57	0.48	0.49	0.47	0.48	0.38	0.41	0.48	0.49	0.48	0.52	0.50	0.51
Graph CodeBERT + TaskAdapter	0.40	0.33	0.35	0.24	0.22	0.23	0.47	0.42	0.43	0.47	0.38	0.40	0.45	0.37	0.40	0.48	0.41	0.43
Graph CodeBERT+LoRA	0.39	0.32	0.35	0.28	0.24	0.26	0.51	0.45	0.47	<b>0.50</b>	<b>0.44</b>	<b>0.45</b>	0.48	0.43	0.44	0.49	0.45	0.46

TABLE IV: The Precision (P), Recall (R), and F1-Score (F1) metrics were assessed on each programming language across various settings. When AdvFusion is combined with Code-LMs, we saw an improved performance in majority of the datasets.

Samples	CodeT5p+Fusion	CodeT5p+AdvFusion	Target
sample 1(Javascript)	Parse a segment of a string .	Parse a segment into a single object .	Parse a segment and convert it into json.
sample 2(Javascript)	Transform a metadata object into a string .	Transform a metadata object into a list of tokens .	Transform token names to formats expected by Sassdoc for descriptions and aliases
sample 3(PHP)	Create a new model .	Create a new database table .	Store new database table.
sample 4(PHP)	Deletes all files in the media picker table.	Cleanup the media picker data	Remove translations images and files related to a BREAD item.
sample 5(Go)	Percentiles returns the percentage of the given number of elements .	Percentiles returns the percentage of the given array of floats .	Percentiles returns percentile distribution of float64 slice.
sample 6(Go)	newPipelineHandler creates a new pipeline handler .	newPipelineHandler returns a new http Handler that will handle the pipeline request .	newPipelineHandler returns a handler for handling raft messages from pipeline for RaftPrefix. The handler reads out the raft message from request body and forwards it to the given raft state machine for processing.

TABLE V: Comparison between CodeT5p+Fusion and CodeT5p+AdvFusion outputs with their ground truth. Samples are selected from the test set results of CodeSearchNet dataset.

no relationship between the size of the language dataset and its contribution to Ruby.

## VII. DISCUSSION

*When should we use adapters for monolingual fine-tuning?*





[37] conducted extensive studies on various PEFT methods, such as Adapters, LoRA, and Prefix-Tuning, evaluated their performance, scalability, and knowledge transfer across more than 100 NLP tasks.

Research on PEFT approaches in software engineering is limited. Authors of [12] conducted an empirical study on natural language to code transferability using adapters. Paper [7] explored PEFT methods like LoRA [15] and Prompt tuning in code generation, focusing on their advantages in large language models compared to small ones. In [38], they analyzed prompt tuning’s impact on CodeBERT and CodeT5 in code tasks like defect prediction, summarization, and translation. They compared fully fine-tuned and prompt-tuned models, assessing accuracy and data efficiency. Other work conducted experimental studies on different PEFT methods for low resource languages on code summarization and code generation [11]. In paper [39], the authors evaluate the performance of PEFT approaches on Just-In-Time Defect Prediction (JIT-DP) and Commit Message Generation (CMG).

### B. Language Models

In the past few years, there is a lot of effort on representing source code using deep learning models for different applications such as code generation [40]–[42], code summarization [1], [2], [32], program synthesis [43]–[46], code search [47], and bug repair [48], [49]. A number of models are also released that are pre-trained on source code and/or code and comment with different objective functions, which are then fine-tuned on multiple downstream tasks [4], [5], [29] such as code summarization [5], [9], [29], [30]. Examples of these models include CodeT5 [29], CodeT5+ [22], PLBART [50], and CodeGPT. Each has versions fine-tuned for specific downstream tasks.

Recent code-focused LLMs include Deepseek-Coder2 [51], CodeLlama [23], an extension of Llama2 [52], and AlphaCode [53], a competition-level code generator. The BigCode community developed StarCoder and StarCoderBase [24], models with 15.5 billion parameters and advanced capabilities like infilling and efficient large-batch inference. Though these large code-LLMs have billions of parameters and differ from models like CodeBERT, Authors of [25] suggest code-LMs perform better than code-LLMs in identifying syntax, making fine-tuning code-LLMs more challenging. In paper [26], it is shown code-LMs often outperform code-LLMs in tasks like clone code detection.

**Differences:** Research on code language models (code-LMs) primarily focuses on program understanding and generation across tasks [40], with limited attention to their adaptability across different languages for specific software engineering tasks. Recent studies explore code-LM transferability for Ruby code summarization [10], using few-shot learning, code-related prompts, or project-specific data [54]–[57]. However, none aim to leverage knowledge from multiple languages for a target language. This paper empirically analyzes monolingual and multilingual adapters for two tasks and proposes an architecture to harness cross-language insights.

## IX. THREATS TO VALIDITY

**External Validity:** This study examines code summarization and method name prediction, focusing on the languages in the CodeSearchNet dataset, which may limit generalizability. We tested our method on CodeT5p, CodeBERT and GraphCodeBERT but performance may vary with other encoder-decoder or decoder-only models. Additionally, the representativeness of CodeSearchNet code samples may not fully capture real-world programming scenarios, affecting the applicability of our findings. **Internal Validity:** Fine-tuning pre-trained models involves selecting a set of hyperparameters which can be complex and lacks a straightforward solution. To mitigate this challenge and ensure robustness, we adopted hyperparameters from [14], which provides an extensive exploration of adapter-specific settings. This reduces potential risks associated with hyperparameter tuning. **Construct Validity:** We evaluate our code summarization model with BLEU-4 score and method name prediction with F1-Score metrics. Choosing metrics is crucial, different ones yield different results. We have selected these metrics based on current literature, minimizing evaluation threats. Please note that, although there are research about the weaknesses of BLEU score for code summarization [58], [59], it is intuitive and easy to understand, as it measures the overlap between the generated translation and one or more reference translations based on n-grams. Secondly, BLEU is language-independent, making it applicable across various language pairs without the need for language-specific tuning. Also, as the results are all reported in the same metric, it is a fair comparison and will not threaten the validity of the results. **Conclusion Validity:** We validated our study’s conclusions by rigorously testing research queries RQ1 and RQ2 with different random seeds and two backbone models. Focusing on code summarization and method name prediction, this process assures the reliability of our findings.

## X. CONCLUSION AND FUTURE WORKS

There is a recent interest in the software engineering research community to use parameter efficient fine-tuning for code-LMs. In this work, we first evaluate and report the performance of AdapterFusion compared to multilingual full fine-tuning. We then introduced AdvFusion, a new architecture that promotes knowledge transfer from other programming languages in a multilingual fine-tuning setting, to enhance the learning capability of AdapterFusion. Using AdvFusion, the performance is on-par with or is improved while involving a smaller parameter budget. The training time is also reduced.

Future directions of this work is applying AdvFusion on other downstream tasks and code-LMs with different architectures. Another avenue could be investigating the reasons that one programming language has a higher attention score to the target task language, compared to other languages. This latter study could open avenues for training models that benefit from other languages for a target task in a low resource language.

## REFERENCES

- [1] J. Gu, P. Salza, and H. C. Gall, "Assemble foundation models for automatic code summarization," *arXiv preprint arXiv:2201.05222*, 2022.
- [2] T. Ahmed and P. Devanbu, "Learning code summarization from a small and local dataset," *arXiv preprint arXiv:2206.00804*, 2022.
- [3] C. Zhang, J. Wang, Q. Zhou, T. Xu, K. Tang, H. Gui, and F. Liu, "A survey of automatic source code summarization," *Symmetry*, vol. 14, no. 3, p. 471, 2022.
- [4] D. Guo, S. Ren, S. Lu, Z. Feng, D. Tang, S. Liu, L. Zhou, N. Duan, A. Svyatkovskiy, S. Fu *et al.*, "Graphcodebert: Pre-training code representations with data flow," *arXiv preprint arXiv:2009.08366*, 2020.
- [5] Z. Feng, D. Guo, D. Tang, N. Duan, X. Feng, M. Gong, L. Shou, B. Qin, T. Liu, D. Jiang *et al.*, "Codebert: A pre-trained model for programming and natural languages," *arXiv preprint arXiv:2002.08155*, 2020.
- [6] T. Y. Zhuo, A. Zebaze, N. Suppattarachai, L. von Werra, H. de Vries, Q. Liu, and N. Muennighoff, "Astraios: Parameter-efficient instruction tuning code large language models," *arXiv preprint arXiv:2401.00788*, 2024.
- [7] M. Weyssow, X. Zhou, K. Kim, D. Lo, and H. Sahraoui, "Exploring parameter-efficient fine-tuning techniques for code generation with large language models," *arXiv preprint arXiv:2308.10462*, 2023.
- [8] J. Liu, C. Sha, and X. Peng, "An empirical study of parameter-efficient fine-tuning methods for pre-trained code models," in *2023 38th IEEE/ACM International Conference on Automated Software Engineering (ASE)*. IEEE, 2023, pp. 397–408.
- [9] T. Ahmed and P. Devanbu, "Multilingual training for software engineering," in *Proceedings of the 44th International Conference on Software Engineering*, ser. ICSE '22. New York, NY, USA: Association for Computing Machinery, 2022, p. 1443–1455. [Online]. Available: <https://doi.org/10.1145/3510003.3510049>
- [10] F. Chen, F. H. Fard, D. Lo, and T. Bryksin, "On the transferability of pre-trained language models for low-resource programming languages," in *2022 IEEE/ACM 30th International Conference on Program Comprehension (ICPC)*. IEEE, 2022, pp. 401–412.
- [11] A. Esmaceli, I. Saberi, and F. H. Fard, "Empirical studies of parameter efficient methods for large language models of code and knowledge transfer to r," *arXiv preprint arXiv:2405.01553*, 2024.
- [12] D. Goel, R. Grover, and F. H. Fard, "On the cross-modal transfer from natural language to code through adapter modules," *arXiv preprint arXiv:2204.08653*, 2022.
- [13] J. Pfeiffer, I. Vulić, I. Gurevych, and S. Ruder, "Mad-x: An adapter-based framework for multi-task cross-lingual transfer," *arXiv preprint arXiv:2005.00052*, 2020.
- [14] J. Pfeiffer, A. Kamath, A. Rücklé, K. Cho, and I. Gurevych, "Adapterfusion: Non-destructive task composition for transfer learning," *arXiv preprint arXiv:2005.00247*, 2020.
- [15] E. J. Hu, Y. Shen, P. Wallis, Z. Allen-Zhu, Y. Li, S. Wang, L. Wang, and W. Chen, "Lora: Low-rank adaptation of large language models," *arXiv preprint arXiv:2106.09685*, 2021.
- [16] H. Rathnayake, J. Sumanapala, R. Rukshani, and S. Ranathunga, "Adapter-based fine-tuning of pre-trained multilingual language models for code-mixed and code-switched text classification," *Knowledge and Information Systems*, vol. 64, no. 7, pp. 1937–1966, 2022.
- [17] N. Houlsby, A. Giurugi, S. Jastrzebski, B. Morrone, Q. De Laroussilhe, A. Gesmundo, M. Attariyan, and S. Gelly, "Parameter-efficient transfer learning for nlp," in *International Conference on Machine Learning*. PMLR, 2019, pp. 2790–2799.
- [18] I. Saberi and F. H. Fard, "Model-agnostic syntactical information for pre-trained programming language models," *arXiv preprint arXiv:2303.06233*, 2023.
- [19] D. Wang, B. Chen, S. Li, W. Luo, S. Peng, W. Dong, and X. Liao, "One adapter for all programming languages? adapter tuning for code search and summarization," *arXiv preprint arXiv:2303.15822*, 2023.
- [20] C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, Y. Zhou, W. Li, P. J. Liu *et al.*, "Exploring the limits of transfer learning with a unified text-to-text transformer," *J. Mach. Learn. Res.*, vol. 21, no. 140, pp. 1–67, 2020.
- [21] X. Hu, G. Li, X. Xia, D. Lo, S. Lu, and Z. Jin, "Summarizing source code with transferred api knowledge," 2018.
- [22] Y. Wang, H. Le, A. Gotmare, N. Bui, J. Li, and S. Hoi, "Codet5+: Open code large language models for code understanding and generation," in *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, 2023, pp. 1069–1088.
- [23] B. Roziere, J. Gehring, F. Gloeckle, S. Sootla, I. Gat, X. E. Tan, Y. Adi, J. Liu, T. Remez, J. Rapin *et al.*, "Code llama: Open foundation models for code," *arXiv preprint arXiv:2308.12950*, 2023.
- [24] R. Li, L. B. Allal, Y. Zi, N. Muennighoff, D. Kocetkov, C. Mou, M. Marone, C. Akiki, J. Li, J. Chim *et al.*, "Starcode: may the source be with you!" *arXiv preprint arXiv:2305.06161*, 2023.
- [25] W. Ma, S. Liu, M. Zhao, X. Xie, W. Wang, Q. Hu, J. Zhang, and Y. Liu, "Unveiling code pre-trained models: Investigating syntax and semantics capacities," *ACM Transactions on Software Engineering and Methodology*.
- [26] S. Dou, J. Shan, H. Jia, W. Deng, Z. Xi, W. He, Y. Wu, T. Gui, Y. Liu, and X. Huang, "Towards understanding the capability of large language models on code clone detection: a survey," *arXiv preprint arXiv:2308.01191*, 2023.
- [27] C. Lee, K. Cho, and W. Kang, "Mixout: Effective regularization to finetune large-scale pretrained language models," *arXiv preprint arXiv:1909.11299*, 2019.
- [28] I. Saberi, F. Fard, and F. Chen, "Utilization of pre-trained language model for adapter-based knowledge transfer in software engineering," *arXiv preprint arXiv:2307.08540*, 2023.
- [29] Y. Wang, W. Wang, S. Joty, and S. C. Hoi, "Codet5: Identifier-aware unified pre-trained encoder-decoder models for code understanding and generation," in *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, 2021, pp. 8696–8708.
- [30] S. Lu, D. Guo, S. Ren, J. Huang, A. Svyatkovskiy, A. Blanco, C. Clement, D. Drain, D. Jiang, D. Tang *et al.*, "Codexglue: A machine learning benchmark dataset for code understanding and generation," *arXiv preprint arXiv:2102.04664*, 2021.
- [31] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," *arXiv preprint arXiv:1412.3555*, 2014.
- [32] P. Nie, J. Zhang, J. J. Li, R. Mooney, and M. Gligoric, "Impact of evaluation methodologies on code summarization," in *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2022, pp. 4936–4960.
- [33] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, "Bleu: a method for automatic evaluation of machine translation," in *Proceedings of the 40th annual meeting of the Association for Computational Linguistics*, 2002, pp. 311–318.
- [34] Y. Tang, C. Tran, X. Li, P.-J. Chen, N. Goyal, V. Chaudhary, J. Gu, and A. Fan, "Multilingual translation with extensible multilingual pretraining and finetuning," *arXiv preprint arXiv:2008.00401*, 2020.
- [35] H. Husain, H.-H. Wu, T. Gazit, M. Allamanis, and M. Brockschmidt, "Codesearchnet challenge: Evaluating the state of semantic code search," *arXiv preprint arXiv:1909.09436*, 2019.
- [36] R. He, L. Liu, H. Ye, Q. Tan, B. Ding, L. Cheng, J.-W. Low, L. Bing, and L. Si, "On the effectiveness of adapter-based tuning for pretrained language model adaptation," vol. abs/2106.03164, 2021. [Online]. Available: <https://api.semanticscholar.org/CorpusID:235359141>
- [37] N. Ding, Y. Qin, G. Yang, F. Wei, Z. Yang, Y. Su, S. Hu, Y. Chen, C.-M. Chan, W. Chen *et al.*, "Parameter-efficient fine-tuning of large-scale pre-trained language models," *Nature Machine Intelligence*, vol. 5, no. 3, pp. 220–235, 2023.
- [38] C. Wang, Y. Yang, C. Gao, Y. Peng, H. Zhang, and M. R. Lyu, "Prompt tuning in code intelligence: An experimental evaluation," *IEEE Transactions on Software Engineering*, vol. 49, no. 11, pp. 4869–4885, nov 2023.
- [39] S. Liu, J. Keung, Z. Yang, F. Liu, Q. Zhou, and Y. Liao, "Delving into parameter-efficient fine-tuning in code change learning: An empirical study," *arXiv preprint arXiv:2402.06247*, 2024.
- [40] Z. Zeng, H. Tan, H. Zhang, J. Li, Y. Zhang, and L. Zhang, "An extensive study on pre-trained models for program understanding and generation," 2022.
- [41] S. Zhou, U. Alon, F. F. Xu, Z. Jiang, and G. Neubig, "Doccoder: Generating code by retrieving and reading docs," *arXiv preprint arXiv:2207.05987*, 2022.
- [42] D. Fried, A. Aghajanyan, J. Lin, S. Wang, E. Wallace, F. Shi, R. Zhong, W.-t. Yih, L. Zettlemoyer, and M. Lewis, "InCoder: A generative model for code infilling and synthesis," *arXiv preprint arXiv:2204.05999*, 2022.
- [43] P. Vaithilingam, T. Zhang, and E. L. Glassman, "Expectation vs. experience: Evaluating the usability of code generation tools powered by large language models," in *CHI Conference on Human Factors in Computing Systems Extended Abstracts*, 2022, pp. 1–7.

- [44] E. Nijkamp, B. Pang, H. Hayashi, L. Tu, H. Wang, Y. Zhou, S. Savarese, and C. Xiong, "A conversational paradigm for program synthesis," *arXiv preprint arXiv:2203.13474*, 2022.
- [45] K. Ellis, C. Wong, M. Nye, M. Sablé-Meyer, L. Morales, L. Hewitt, L. Cary, A. Solar-Lezama, and J. B. Tenenbaum, "Dreamcoder: Bootstrapping inductive program synthesis with wake-sleep library learning," in *Proceedings of the 42nd acm sigplan international conference on programming language design and implementation*, 2021, pp. 835–850.
- [46] J. Austin, A. Odena, M. Nye, M. Bosma, H. Michalewski, D. Dohan, E. Jiang, C. Cai, M. Terry, Q. Le *et al.*, "Program synthesis with large language models," *arXiv preprint arXiv:2108.07732*, 2021.
- [47] U. Nadeem, N. Ziem, and S. Wu, "Codedsi: Differentiable code search," *arXiv preprint arXiv:2210.00328*, 2022.
- [48] C. Richter and H. Wehrheim, "Can we learn from developer mistakes? Learning to localize and repair real bugs from real bug fixes," *arXiv e-prints*, p. arXiv:2207.00301, Jul. 2022.
- [49] J. Zhang, S. Panthaplackel, P. Nie, J. Jessie Li, and M. Gligoric, "CoditT5: Pretraining for Source Code and Natural Language Editing," *arXiv e-prints*, p. arXiv:2208.05446, Aug. 2022.
- [50] W. Ahmad, S. Chakraborty, B. Ray, and K.-W. Chang, "Unified pre-training for program understanding and generation," in *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 2021, pp. 2655–2668.
- [51] Q. Zhu, D. Guo, Z. Shao, D. Yang, P. Wang, R. Xu, Y. Wu, Y. Li, H. Gao, S. Ma *et al.*, "Deepseek-coder-v2: Breaking the barrier of closed-source models in code intelligence," *arXiv preprint arXiv:2406.11931*, 2024.
- [52] H. Touvron, L. Martin, K. Stone, P. Albert, A. Almahairi, Y. Babaei, N. Bashlykov, S. Batra, P. Bhargava, S. Bhosale *et al.*, "Llama 2: Open foundation and fine-tuned chat models, 2023," URL <https://arxiv.org/abs/2307.09288>, 2023.
- [53] Y. Li, D. Choi, J. Chung, N. Kushman, J. Schrittwieser, R. Leblond, T. Eccles, J. Keeling, F. Gimeno, A. Dal Lago *et al.*, "Competition-level code generation with alphacode," *Science*, vol. 378, no. 6624, pp. 1092–1097, 2022.
- [54] T. Ahmed and P. Devanbu, "Few-shot training LLMs for project-specific code-summarization," *arXiv e-prints*, p. arXiv:2207.04237, Jul. 2022.
- [55] P. Bareiß, B. Souza, M. d'Amorim, and M. Pradel, "Code Generation Tools (Almost) for Free? A Study of Few-Shot, Pre-Trained Language Models on Code," *arXiv e-prints*, p. arXiv:2206.01335, Jun. 2022.
- [56] M. Khajezade, F. Hendijani Fard, and M. S. Shehata, "Evaluating few shot and Contrastive learning Methods for Code Clone Detection," *arXiv e-prints*, p. arXiv:2204.07501, Apr. 2022.
- [57] T. Ahmed and P. Devanbu, "Learning code summarization from a small and local dataset," *arXiv e-prints*, p. arXiv:2206.00804, Jun. 2022.
- [58] D. Roy, S. Fakhoury, and V. Arnaudova, "Reassessing automatic evaluation metrics for code summarization tasks," in *Proceedings of the 29th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, 2021, pp. 1105–1116.
- [59] S. Haque, Z. Eberhart, A. Bansal, and C. McMillan, "Semantic similarity metrics for evaluating source code summarization," in *Proceedings of the 30th IEEE/ACM International Conference on Program Comprehension*, 2022, pp. 36–47.