

# Scaling Down Multi-Lingual Code Language Models

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# Abstract

The democratisation of AI and access to code language models have become pivotal goals in the field of artificial intelligence. Large Language Models (LLMs) have shown exceptional capabilities in code intelligence tasks, but their accessibility remains a challenge due to computational costs and training complexities. This paper addresses these challenges by presenting a comprehensive approach to scaling down Code Intelligence LLMs. To enhance usability, we focus on training smaller code language models, which lowers the computation cost of inference and training. We extend these models to diverse programming languages, enabling code completion tasks across various domains. Additionally, we explore the impact of different choices in fine-tuning LLMs, providing empirical evidence on training efficiency in terms of time, cost, and performance.

In pursuit of these goals, we fine-tune a Python-based mono-lingual code LLM for Java, Rust, Ruby, and Swift. Utilising the LoRa Parameter Efficient Fine-Tuning technique, we share these models, their training datasets, and evaluation results openly. Extensive ablation studies, trade-off analyses, and error assessments shed light on the effects of training process choices. This work contributes to the democratisation of AI by making Code LLMs more accessible and usable for practitioners. By addressing computational barriers and providing insights into training dynamics, we bridge the gap between AI development and practical application, fostering an environment where code intelligence tools can be readily adopted.

**Keywords:** Large Language Models, code intelligence, democratisation of AI, fine-tuning, programming languages

# **Research Ethics Approval**

This project was planned in accordance with the Informatics Research Ethics policy. It did not involve any aspects that required approval from the Informatics Research Ethics committee.

## **Declaration**

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

*(Ammar Khairi)*

# Acknowledgements

Any acknowledgements go here.

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# Chapter 1

## Introduction

### 1.1 Motivation

In recent years, Large Language Models (LLMs) have emerged as powerful tools with applications spanning various domains. Notably, their effectiveness in code intelligence tasks has been remarkable, leveraging the structured and rule-based nature of programming languages. There are three areas that can be considered the main drivers for the success of LLMs: (i) Model architectures: Transformers are capable yet simple models as they rely on the self-attention mechanism. (ii) Learning Algorithms: The Pre-training and Fine-tuning learning algorithms made models more fixable for handling a number of specialised tasks (iii) Scale: better performance can be expected by increasing the model parameters, the data, or the computation according to the scaling laws. These discoveries have resulted in excellent performance in program synthesis and understanding challenges and have been adapted to both commercial [15] and open-source [30] tools.

Accessibility to code language models is one of the important goals of AI development. The Democratization of AI is an important factor in the progress of the field, and AI companies such as Meta [2] and Stability-AI [3] are showing their commitment to it by publicly sharing their models and releasing their weights. However, this may not be enough, as the barrier to tuning and using LLM is higher than access to their weights. For the practitioner, the choices of model architecture and learning algorithm are not obvious, and exploring these options is costly due to the high computation costs. In order to achieve the benefits of democratization of AI use and development [45], these issues need to be resolved.

## 1.2 Problem Statement

The aim of this project is to address the accessibility gap and further efforts towards democratising the use and development of code LLMs. To make LLMs more usable, we need to first address the high computational cost of large language models. Using smaller models also comes with the cost of being limited to a small number of popular programming languages. Hence, We will train small code language models to perform code completion tasks [32] in a variety of programming languages. Additionally, to address the ambiguity in fine-tuning LLMs, we will provide empirical evidence on the effects different choices have on the training process in terms of time, cost, and performance.

## 1.3 Contribution

In this work, We extend the capabilities of a mono-lingual code LLM originally trained on Python to encompass a diverse range of programming languages including Java, Rust, Ruby, and Swift. This expansion is achieved efficiently by employing Parameter Efficient training techniques and various training optimization methods. All the models are shared publicly along with their respective training datasets and evaluation results. We also did extensive ablation studies, trade-off computations, and error analysis to provide empirical evidence on the effects different choices in the training process have on the efficiency of the process. Finally, we discussed the current state of AI democratisation, the associated risks and benefits, current gaps, and possible ways forward.

## 1.4 Thesis Structure

This paper will be divided into the following five parts:

- The project’s motivation, goals, and outcomes are primarily introduced in the first chapter, which also serves as an introduction. This chapter provides a general overview of the project, highlights its innovation and significance, and discusses its ultimate objective.
- The background primarily introduces prior research and work in the project’s pertinent fields. In order for readers to become familiar with the project and better



comprehend the works produced by this project.

- The methodology chapter provides a detailed introduction to each step of the project's implementation as well as the project's overall structure. Additionally, it goes into detail about how pipelines are built for data preprocessing, various methods of fine-tuning, and evaluation.
- The result and evaluation are covered in chapter four. The experiments conducted for the project will be covered in this chapter. This will include each experiment's goal, setup, and outcomes, as well as an evaluation of these outcomes.
- The fifth chapter is a summary, which will summarise the contributions of the projects in terms of AI democratization and discuss the benefits, risks, and ways forward for more accessible code language models.

# Chapter 2

## Background

This chapter is meant to present the reader with the necessary context for this project, which aims to democratize the use of code language models by efficiently training monolingual smaller models. We will begin by providing an overview of approaches for efficient training of large language models, as well as their impact on memory, run-time, and performance. Then we discuss the present state of the art in using multilingual code language models for code completion tasks. Finally, we review current trends and initiatives in the topic of AI democratization briefly.

### 2.1 Efficient Training Methods

Scaling is a critical component in reaching state-of-the-art performance in NLP, since recent research suggests that greater model size can result in predictable performance benefits [52]. Despite the benefits of scaling, it creates significant hurdles to making these advances available in resource-constrained situations [6]. To address these limitations, there has been a renewed emphasis on research aimed at improving model efficiency [49].

When implementing efficient training methods, there are many factors to consider. The work of [44] defines efficiency as the cost of producing a result( $R$ ) in terms of three factors: execution cost( $E$ ), dataset size ( $D$ ), and the number of Hyperparameters( $H$ ):  $Cost(R) \propto E \cdot D \cdot H$ . On the other hand, [48] examines several efficiency strategies based on their effects on model precision, the number of computations (FLOPS), and total memory need. We will use a similar approach to [44] and compare approaches based on the previous criteria and whether a method is for training, inference, or both, as shown in Table 2.1.

The methods in Table 2.1 cover a variety of techniques. Sparsity [35] is a technique that aims to reduce the memory footprint of training models by dynamically adding sparse connections (zero parameters) through the training. Sparse matrix operations can be optimised to save memory, but their effect on the run-time is unclear [54]. Quantization techniques use the 16-bit representation of floats instead of the 32-bit representation to achieve a 2x reduction in memory requirements and speed up the computations [27]. The work of [33] studies the trade-off when using smaller batch sizes (micro-batching) between reduction in memory and reduction parallelism. The effect of micro-batching also varies, as smaller batches could improve generalisation, while larger batch sizes may result in more stable learning, both depending on other factors like the learning rate and normalisation techniques [33], [16]. The work of [18] takes a different approach by addressing self-attention quadratic time and memory complexity with sequence length. Flash-Attention is an optimised I/O aware (uses fewer accesses to GPU memory) that achieves up to 7.6x speedup and a linear memory to sequence length complexity. This method was the foundation that enabled the training of LLMs with very large context windows [39]. Pruning and trained quantization [22] are model compression methods that can be used to enable inference on memory poor edge devices.

Parameter’s Efficient Fine-Tuning (PEFT) is central to the pre-training and fine-tuning paradigm for large language models, as fully fine-tuning LLMs requires significant time and resources. The goal of PEFT approaches is to optimise LLMs by modifying lightweight trainable parameters while leaving the majority of pretrained parameters unchanged. PEFT approaches vary; for example, the adapter method [25] adds trainable parameters to each transformer block of the model. Another technique known as prompt-tuning [29] relates to techniques that modify the input prompt to improve modelling results. Finally, LoRa [26] learns low-rank matrices to approximate the weight updates of the LLM.

## 2.2 Code Completion Using LLMs

**Code LLMs** Using language models for code generation and comprehension tasks has recently received a lot of attention. Large language models for code can be divided into three groups: masked language models, encoder-decoder models, and left-to-right language models. Masked LLMs, such as CodeBert [19], are used to provide representations for code sequences, which are useful in code comprehension tasks like

| Method                 | Memory | Runtime | Performance | Training | Inference |
|------------------------|--------|---------|-------------|----------|-----------|
| Sparsity               | ↓      | ?       | ↓           | ✓        | ✓         |
| Quantization           | ↓      | ↓       | -           | ✓        | ✓         |
| Micro-Batching         | ↓      | ↑       | ?           | ✓        | -         |
| Gradient checkpointing | ↓      | ↑       | -           | ✓        | -         |
| FlashAttention         | ↓      | ↓       | -           | ✓        | ✓         |
| Pruning                | ↓      | ↓       | -           | -        | ✓         |
| Trained Quantization   | ↓      | ↓       | -           | -        | ✓         |
| PEFT                   | ↓      | ↓       | ↓           | ✓        | -         |

Table 2.1: Summary of Efficient Training Methods

clone detection and code classification. CodeT5 [51] is an encoder-decoder model that can be used for conditional generation tasks like code generation from natural languages. The work of [17] has demonstrated that left-to-right code (decoder only) language models, such as SantaCoder[8] and PolyCoder [53], perform exceptionally well on a wide range of tasks, including code generation and completion.

**Evaluating Generations** Code completion can be evaluated intrinsically through textual similarity metrics or extrinsically through execution-based metrics. Intrinsic evaluation measures such as CodeBLEU [43] and perplexity are simple to calculate and language agnostic. These measurements, however, have been demonstrated to have a small correlation with code generation quality [15]. Most execution-based metrics are composed of a set of code challenges, each with its own natural language description, function signature, and set of unit tests. HumanEval [15] and the Mostly Basic Programming Problems (MBPP) [11] are two of the most commonly used execution metrics, and both are Python-based. There are, however, a number of works that extend both metrics into additional programming languages. MultiPl-E [14] adds 18 new languages to HumanEval and MBPP, whereas [10] adds over 10 new programming languages to HumanEval, MBPP, and Math-QA [9]. Finally, the BabelCode and TP3 [40] benchmarks give fine-grained (unit test level) code completion evaluation in 14 different programming languages.

## 2.3 AI Democratisation

In recent years, there has been a significant increase in the conversation about "AI democratisation." However, the term itself is used in various ways, leading to a lack of clear communication among experts when talking about the objectives, approaches, potential dangers, and advantages of initiatives aimed at achieving AI democratisation [46]. The work of [7] refers to AI democratisation solely on the basis of the decentralisation of knowledge production in the field. Whereas [46] identifies four types of AI democratisation: democratisation of use, development, governance, and profits. The term participation is often used to highlight the importance of centering the values of all agents affected by the development of AI [12].

These different explanations of the term are partly due to the different motivating factors for pursuing AI democratisation. The uneven distribution of AI harm due to inherent biases [13] is one of the most important reasons behind the increased interest in inclusive AI development. Another reason is that increased contributions from around the world are essential to the progress of the field. Finally, The work of [7] and [24] advocates scaling down so that ideas are not pushed aside for lack of compatibility with available compute.

Current trends towards AI democratisation also vary greatly. Open-source models and datasets are the most efficient way of facilitating wide and diverse inclusion in AI development [36]. Additionally, as we discussed in Section 2.1, scaling down and lowering the barrier to entry are also being heavily researched. Finally, some works also propose solutions based on policies that enforce and encourage democratisation. such as calls for national research cloud [4].

# Chapter 3

## Methodology

### 3.1 Project Methodology Overview

The main objective of this project is to make access to code intelligence models easier in terms of use and development. Because of this, the project’s overall structure is designed to be straightforward and modular, allowing practitioners to easily follow and reproduce any part of it. The diagram in 3.1 demonstrates how the project’s steps progress from choosing a baseline model and processing the training dataset to evaluating and disseminating the final model weights and card. While the sections that follow in this chapter will go into more detail about particular parts, this section will provide an overview of how these parts relate to one another.

The first step in the pipeline in Figure 3.1 is the selection of the baseline model that will be fine-tuned. Any auto-regressive language model can be chosen at this stage because the fine-tuning task is causal language modelling. However, we only use the CodeGen-350M-mono [38] because it is a small and monolingual code language model trained only on Python. Processing the training dataset is the next step. The sampling of training data from the TheStack corpus [28], file filtering, and generation of the training and validation splits were all standardised in this step. Any programming language chosen for this step will be subject to all of these operations.

The fine-tuning process can start once the training dataset and baseline model are available. This stage has the largest number of possible parameter configurations, but the main options are between full fine-tuning and LoRa fine-tuning. The fine-tuning can be completed on a free Google Colab T4 GPU [1] in less than 10 hours, depending on the method and parameters chosen. After completion, the weights and training metrics are all saved for use in the evaluation stage. The evaluation is also divided into

two stages. The first stage is the generation stage, where model outputs are produced according to specific prompts and inference parameters. The second stage is using these generations to create an evaluation report with different results and analyses. Finally, when all the outputs are available, model cards [34] and dataset cards [21] are automatically generated to be shared with the model on open source platforms such as HuggingFace [5] (Figure 3.2).

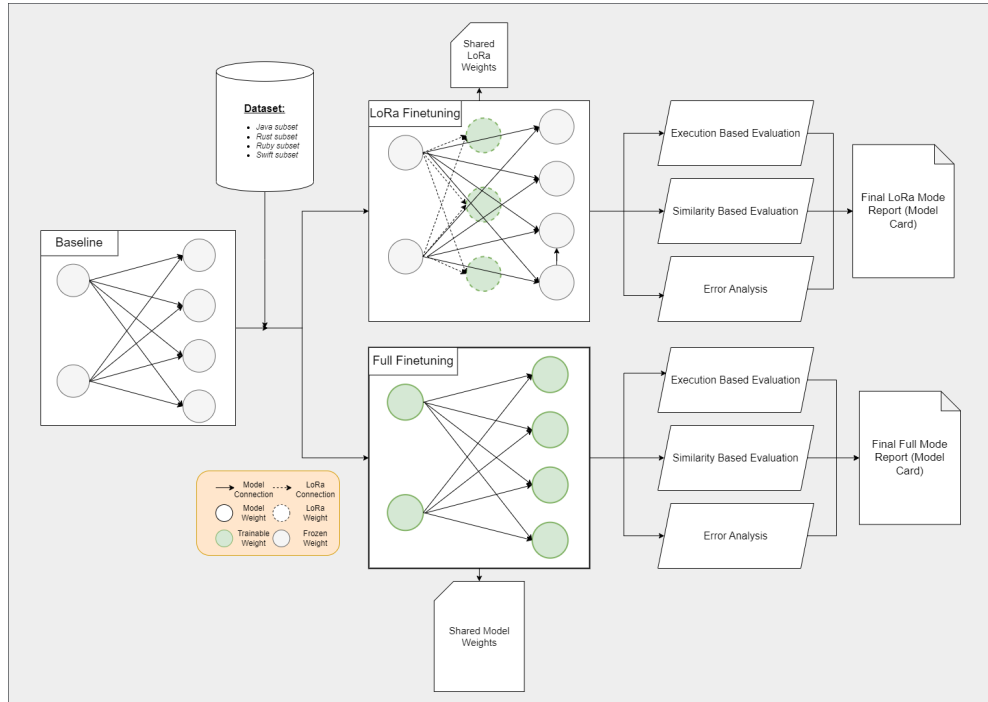


Figure 3.1: Project Diagram

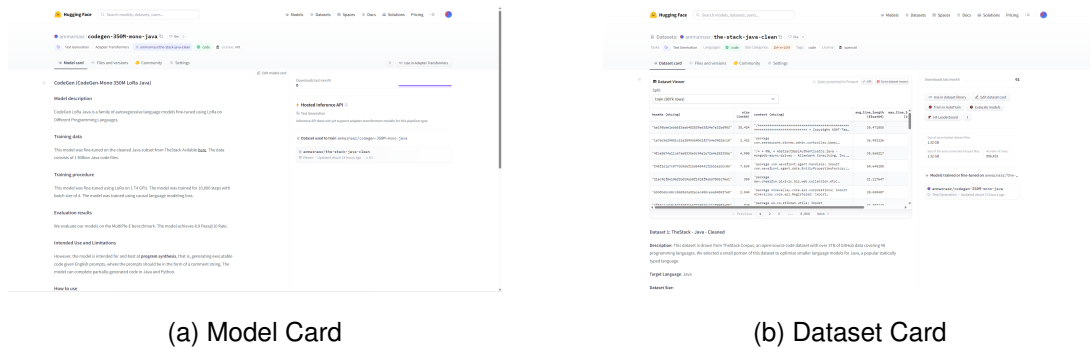


Figure 3.2: Example Of Generated Model and Dataset Cards Shared on HuggingFace

## 3.2 Dataset

Our training datasets are primarily drawn from TheStack Corpus [28]. TheStack is an open-source code dataset with more than 3TB of GitHub data covering 48 different programming languages. We only use a small portion of this dataset because our experiments only consider a small subset of programming languages and because optimising smaller language models only needs a small amount of data.

We had to perform several preprocessing steps in order to prepare our datasets. The first step is choosing our target programming languages. Ruby, Swift, Rust, and Java were ultimately chosen. We selected these languages because they represent the distribution of programming languages on GitHub. As seen in figure 3.3a, the most popular language is Java; Ruby and Rust are medium-resource languages, and Swift is a low-resource language. Additionally, Ruby was chosen because it shares syntax similarities with Python and is a dynamic language, whereas Java, Rust, and Swift are all statically typed. The next step is to select a sample of files from TheStack corpus and divide them into train, validation, and test splits. In order to train LLMs effectively, we sampled one million files from each of the four languages. To filter the files, we adhered to best practises [53] and filtered out files with the following characteristics: 1) an average line length of over 100 characters; 2) a maximum line length of over 1000 characters; and 3) a ratio of alphabet less than 25%. Then, we split the remaining files into train, validation, and test splits using ratios of 0.9, 0.05, and 0.05. Figure 3.3b shows the statistics for the final datasets.

The tokenizers used were the same as those for the baseline models [38]. These Byte Pair Encoding (BPE) [47] tokenizers add special tab and white space tokens to the same GPT-2 vocabulary [42]. The training sequences are produced by joining text from training data to fill the 2048 context length, or just 1024 tokens in the case of full fine-tuning.

## 3.3 Baseline Model

The careful selection of the baseline model is important in the context of this project, as it fundamentally underpins the subsequent phases of our fine-tuning methodology. In this section, we discuss our choice of the CodeGen-350M-Mono as our designated baseline model, offering a short analysis of its distinctive attributes and limitations.

The compactness of CodeGen-350M-Mono at 350 million parameters was a pivotal



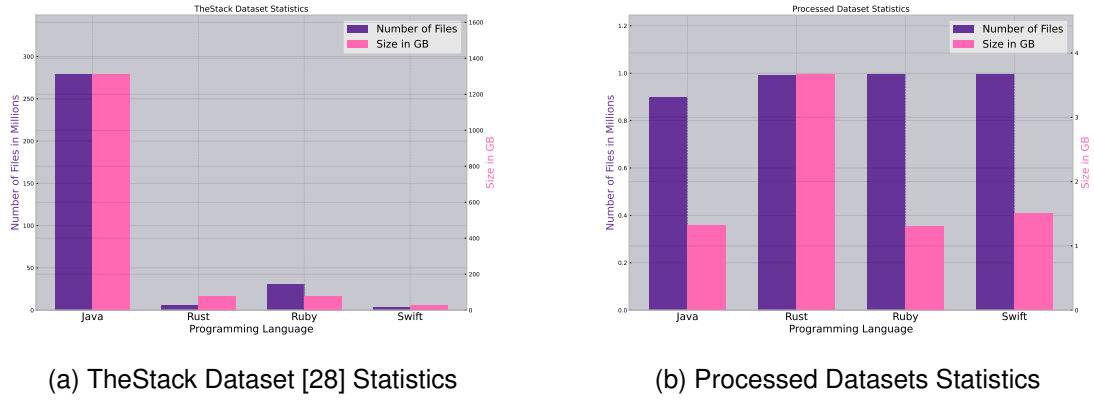


Figure 3.3: Comparison Of Datasets before and after Processing

factor in the choice of the CodeGen model family as our baselines [38], [37]. The advantage of a compact model extends beyond the immediate computational efficiency gains when fine-tuning. Small models are more friendly in deployment and dissemination, enabling swifter accessibility and utilisation for a diverse array of practitioners.

Additionally, the CodeGen-350M model family includes equivalent multilingual models that share the same architecture and training procedures as the monolingual models. This inherently positions CodeGen-350M-Multi as a robust benchmark against which to measure the efficacy of our proposed approach. A notable drawback of the monolingual baseline is that its weights were initialised using a model trained on a corpus including a mix of programming languages and natural languages [20]. This limitation, however, applies to practically all code language models because it is considered standard practise in the area [53].

### 3.4 Training Objective

In this section, we will briefly discuss the training objective we used for fine-tuning the code language models to new programming languages. The self supervised autoregressive language modelling approach is used for both complete fine tuning and LoRa fine tuning. In this approach, we take a large corpus of unlabeled text and set up a task to predict the next word based on the words that came before. Mathematically, the training objective is expressed as the minimization of a loss function:

$$\mathcal{L} = - \sum_{t=1}^T \log P(x_t | \mathbf{x}_{<t}) \quad (3.1)$$

In this equation,  $\mathcal{L}$  represents the loss incurred during training,  $T$  signifies the

sequence length, and  $x_t$  denotes the token at position  $t$ . The conditional probability  $P(x_t|\mathbf{x}_{<t})$  captures the likelihood of the observed token given the preceding context, encapsulating the essence of the masked language modeling task. Notably, in the context of code generation, the token sequence  $\mathbf{x}$  encompasses either code fragments to be completed or natural language instructions that require translation into code.

### 3.5 Full Fine-tuning

The concept of full fine-tuning forms a cornerstone of the pre-train and fine-tune paradigm, a principle that has exhibited remarkable efficacy in a multitude of natural language processing tasks. In this section, we delve into the essence of full fine-tuning, outlining its basic functioning and highlighting its role in developing code intelligence models with task-specific skills.

Full fine-tuning entails the comprehensive retraining of all model parameters for a specific downstream task. This approach gained increased popularity after Bert showed its applicability to a wide range of NLP tasks. Bert’s work also introduced feature fine-tuning, wherein only a subset of model layers are fine-tuned. Our work considers full fine-tuning to investigate the inherent trade-off when using the method to tailor large language models to specific tasks. The main advantage of full fine-tuning is the enhanced model flexibility and convergence speed that arise from the large number of trainable parameters. On the other hand, the computational resources demanded by these extensive parameters pose significant challenges.

### 3.6 Efficient Fine-tuning

Efficiency stands out as a cardinal principle in the realm of training large language models. This section is dedicated to breaking down the technicalities of efficient fine-tuning, encapsulating both Parameter-Efficient-Fine-Tuning (PEFT) strategies and training optimisation techniques. Through this exploration, we illuminate the intricate mechanisms that enable us to harness the potential of code intelligence models while mitigating the resource-intensive nature of their training.

The first facet of efficient fine-tuning centres around parameter-efficient fine-tuning (PEFT). This direction relies on optimising the fine-tuning process by reducing the number of trainable parameters. A central pillar of PEFT is The Low-Rank Adaptation Method (LoRa). This approach employs a method where it fixes the pre-trained model

weights and introduces adaptable rank decomposition matrices into different layers of the Transformer architecture. Hence, it significantly minimises the number of trainable parameters. When compared to the fine-tuned GPT-3 175B using full fine tuning, LoRA achieves a 10.000x reduction in the number of trainable parameters and a 3x decrease in GPU memory requirements. Finally, LoRA demonstrates comparable performance to full fine-tuning on various large language models, with fewer parameters and without introducing inference latency like other PEFT methods such as Adaptors.

The second dimension of efficient fine-tuning addresses the optimisation of the training process. In Section Background, we show the variety of methods available; however, we will only use three of them: Quantization, Gradient Check-pointing, and Gradient Accumulation. These techniques, while distinct in their mechanisms, converge in their shared goal of enhancing training efficiency by minimising memory limitations. Quantization refers to the execution of some or all of the operations on tensors with reduced precision rather than full precision (floating point) values. This allows for a more compact model representation and the use of high performance vectorized operations on many hardware platforms. In the context of fine tuning code language models, this allows to half the resource requirement (when 16-bit representation is used instead of 32-bit representation) without significantly affecting the precision of our model.

Most of the memory requirements when training code language models come from the optimizer's saved states during back propagation. Gradient check-pointing allows us to minimise the memory footprint of the optimizer at the cost of an extra forward pass per batch, which significantly slows down training. Finally, we use Gradient accumulation to achieve a larger effective batch size without increasing the memory cost by accumulating smaller mini batches. This method also has a significant overhead in terms of computation. Throughout the project, we use these methods in various combinations based on the objective of the experiment and the other parameters.

## 3.7 Inference and Evaluation

**From IPP** *Assessing the ability of models to generate code is a crucial aspect of research in this field. There are two main methods for evaluation in the literature: match-based and execution-based evaluations. In both approaches, a prompt is given to a model, which uses it to create a code solution. The match-based evaluation method measures the similarity between the candidate code and a reference code using n-gram metrics like*

*Perplexity (PPL). Perplexity is a commonly used metric in natural language processing (NLP) for measuring how well a language model predicts a sample. Presented with a well-written code sample, a good code language model should be able to give it a high probability equivalent to a low PPL value. On the other hand, the execution-based evaluation method executes the candidate code using test cases and measures the success rate. The execution-based evaluation method has an advantage over the match-based evaluation method in that it allows for functionally correct solutions that may not match the reference solution exactly in terms of implementation. However, execution based dataset creation is far more expensive than match-based ones. This is due to the fact that verifying the correctness of execution requires careful specification of test cases and prompts. As a result, there are currently only a few execution benchmarks available, such as the Mostly Basic Programming Problems (MBPP) [?] and the HumanEval [15] datasets. Both of these benchmarks are in Python but have been translated to other programming languages, either manually [?] or automatically [?]. Translating benchmarks may result in smaller or less accurate datasets, a shortcoming that we need to consider. Given this context, we have decided to use both execution and match-based evaluations since we are using Python as our primary language and Java as our secondary language. This approach will help us compensate for errors in translating prompts and test cases, as some studies have shown a positive correlation between the two evaluation schemes [?], despite the limitations of the match based scheme [?]. Furthermore, in addition to direct quantitative comparisons, we plan to analyse the results in several ways. Firstly, we will evaluate the efficiency of training in terms of computation, time, and number of parameters. Next, we will investigate how fine-tuning for a specific language can affect performance in other programming languages. Finally, we will conduct a qualitative assessment by examining samples that have real-world value, such as code snippets from dynamic programming languages compared to snippets from typed languages.*

# Chapter 4

## Results and Evaluation

In this chapter, we will cover all the experiments in the project, discussing the objectives of each experiment, the experimental setup, and then presenting and analysing the outcomes. The chapter will be divided into four sections, where each section builds on the previous results and presents experiments with similar objectives. In the first section, we compare Full fine tuning methods vs. efficient fine-tuning methods and try to find out the difference in performance we can achieve in the Java programming language. Next, we perform ablation studies on the parameters of LoRa fine-tuning to understand the contribution of each factor to the process. In Section 4.3 we study the trade-off between memory, time, and performance when fine-tuning code language models in an environment with limited resources. Finally, we use the knowledge obtained from previous results to train models on programming languages other than Java, and in the final section, we perform error analysis on the generations of these models.

### 4.1 Full Fine-Tuning vs. Efficient Fine-Tuning

#### 4.1.1 Objective and Setup

We suggest that a possible solution to the high inference and training costs of Large Language Models is to use smaller, more compact architectures. However, this also comes at a cost, as smaller models are normally trained in only one programming language to achieve good performance with their limited parameters. In fact, work by [10] has empirically shown that training sufficiently large language models benefits the model's overall performance as knowledge can be transferred between different languages. On the other hand, training smaller models in an increasing number of

programming languages hinders learning in all of them.

However, we hypothesise that it is possible to fine-tune small mono-lingual language models to perform satisfactorily well in other programming languages. We argue that one can use full fine-tuning and utilise the trained model weights as initialization with knowledge about general programming knowledge and natural language. Full fine-tuning, however, suffers from the phenomenon known as catastrophic forgetting [50], which may cause the tuned model to forget the syntax of its original programming language. Using parameter-efficient techniques, we can mitigate the forgetting issue and reduce the computational cost. These gains come from only a small number of low rank matrices, which, on the other hand, may limit the learning ability of the model.

We used the task of code completion, particularly the one outlined by [15], to test our hypothesis. We used the Codegen-350M-mono and Codegen-350M-multi auto-regressive code language models developed and released by Codeforce as baselines [38]. Both models share the same number of parameters (350 million) and structural elements. The difference is that the mono version is trained on Python only (BigPython [38]), and the multi version is trained on a mix of four languages (Python, Java, JavaScript, and C) from TheStack dataset [28]. Then, we fine-tuned the mono model on the Java subset of the preprocessed dataset discussed earlier. We employed Full and LoRa fine-tuning using the same casual language modeling objective [41], Adam optimizer, a 0.0005 Learning rate with cosine decay, and an effective batch size of 8. The maximum sequence length in full fine tuning was 1024, and in LoRa it was 2048 due to memory limitations. A detailed description of these parameters is in the ablation studies Section 4.2.

### 4.1.2 Analysis

The results in Figure 4.1 show that it is possible to fine-tune monolingual models for new programming languages in a reasonable amount of time with limited computational resources. As shown in figure 4.2, the training lasted for 10,000 steps, or the equivalent of 80,000 different files, each with 1024 and 2048 Java tokens for Full and LoRa fine-tuning, respectively. The training was done on a Google Colab T4 15GB GPU and lasted for around 12 hours.

The Loss curves in figure 4.1 show that the LoRa fine-tuned model evaluation loss flattened earlier than the full fine-tuned one. But the latter had a lower evaluation loss overall. In Figure 4.2, we see the differences more clearly The pass@10 rate of the full

fine-tuning is 50% higher than LoRa and, in fact, almost the same as the results from the multilingual baseline, which saw a much larger number of Java tokens.

We can also see from Figure 4.2 the effects of catastrophic forgetting, as the Python score for full-fine-tuning is 0.0 while the LoRa score is 3.75, which is also a significant drop from the 22.36 in the monolingual baseline. Additionally, we see that even though the monolingual baseline was only trained on Python, it still passes some of the Java problems. This is probably due to code spill (Java code inside Python files), and it has been reported in other works [10].

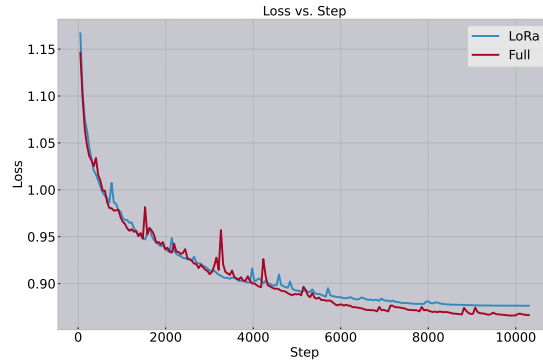


Figure 4.1: Comparison of Loss Curves for LoRa and Full Fine Tuning

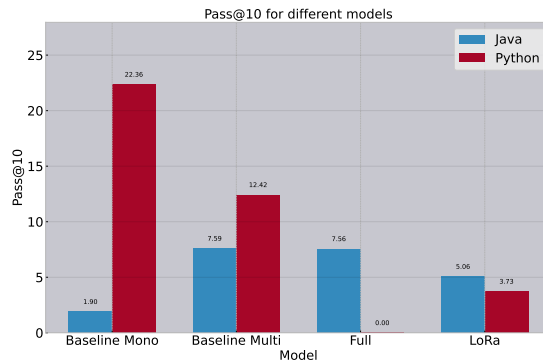


Figure 4.2: Comparison of Pass@10 for LoRa and Full Fine Tuning vs the Baselines

## 4.2 Ablation Studies

### 4.2.1 Objective and Setup

As we discussed in previous sections, fine-tuning entails selecting a large number of parameters. Choosing an acceptable parameter configuration might be a challenge for

practitioners trying to fine-tune their own code language models. Even when employing smaller models and efficient fine-tuning approaches, the exploration cost remains significant due to the fact that knowledge about the effects of most of these parameters is still vague in the field [37], [40]. Furthermore, the effects of these parameters are subject to change due to changes in external variables such as model size, data quality, or downstream tasks [23]. Finally, In circumstances like ours, when we focus on efficiency measures (Memory and Time) as well as performance on a specific activity, parameter selection becomes more challenging.

We conducted comprehensive ablation studies in this experiment to provide empirical evidence that practitioners can use to guide parameter selection. We study the effect a selected number of parameters have on the efficiency and performance of fine-tuning code language models with LoRa. The following parameters have been chosen: LoRa Rank, LoRa layers, Batch Size, Sequence Length, and Learning Rate. In the following section, we will go over each parameter, justifying why we chose it, the expected behaviour, and our findings. We configured our experiments to use the same baseline model and fine-tuning settings as our first experiment in Section 4.1. Then, for each of the ablation variables, we repeat the fine-tuning process across a fixed number of tokens. In each of these runs, we gradually adjust the variable and examine the effects of the fine-tuning process on performance and efficiency.

### 4.2.2 Analysis

**LoRa Rank** This variable relates to the rank of the decomposed matrix that will be optimized rather than the high rank weight matrix of the model. The choice of this value immediately translates to the number of trainable models in the model and, thus, the efficiency and quality of the fine-tuning process. According to [26] findings, even low rank values (2 or 3) can achieve good performance, and increasing the rank can also improve performance. We expected similar behaviour when fine-tuning our code language models. To test this hypothesis, we choose a range of ranks (8, 16, 32, 64, 128), then train and evaluate our baseline for 1000 steps on the Java dataset (as we will do in all the ablation studies). The values chosen for LoRa Rank range from %0.8 trainable parameters to 12% of the model's total parameters 4.1. Figure 4.3a shows that the evaluation loss remains consistent as the rank increases, against what we expected. This can be explained by the fact that beyond a certain rank size, the matrices injected as approximation to weights update are effectively equivalent. Finally, Figure



| Rank | Trainable Parameters | Percentage |
|------|----------------------|------------|
| 8    | 3214336              | 0.893%     |
| 16   | 6253568              | 1.724%     |
| 32   | 12332032             | 3.343%     |
| 64   | 24488960             | 6.427%     |
| 128  | 48802816             | 12.040%    |

Table 4.1: Different Lora Ranks Number of Parameters

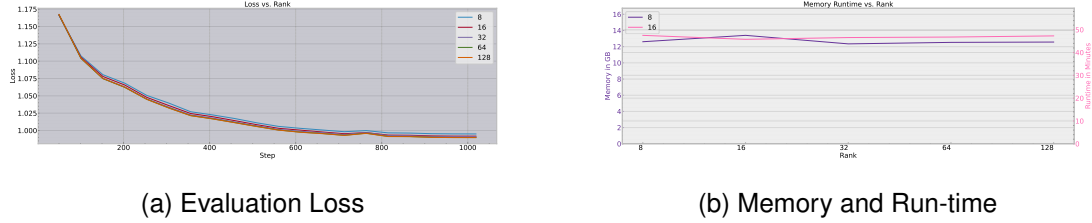


Figure 4.3: Performance and Efficiency For Different LoRa Ranks

4.3b indicates that the increased number of trainable parameters has no influence on efficiency; the difference in parameters is insignificant in terms of processing even up to almost 50 million parameters.

**LoRa Target Modules** These modules refer to specific components within the LoRa framework that are targeted for optimisation during the fine-tuning process. The selection of target modules plays a crucial role in determining the overall impact of optimisation on the model's performance. For example, focusing on modules related to the vocabulary distribution ("lm\_head") might yield different results compared to targeting modules responsible for semantic understanding ("qkv\_proj"). Additionally, different modules affect the efficiency of the training differently, as each module has a specific size and number of blocks in the model. Table 4.2 summarises the selection of modules for this experiment and the number of trainable parameters for each. The results in Figure 4.4 show that best performance is achieved when we insert LoRa parameters across all layers of our model (*Conf-7*). It can also be seen that the gains in performance from the inclusion of Fully connected with the attention modules (*Conf-4*, *Conf-5*, *Conf-6*) are significantly higher than including specific language specific layers (*Conf-1*, *Conf-2*, *Conf-3*). Regarding efficiency measures in Fig 4.5 we see the different modules choices have minimal effect on the run-time. However, In terms of memory usage , the addition of fully connected modules requires results in less memory usage than adding language feature layers, even though the latter have fewer parameters.

| Index | Modules  | Trainable Parameters | Percentage | Comments |
|-------|--|----------------------|------------|----------|
| 0     | ["qkv_proj"]   | 5417984              | 1.497%     |          |
| 1     | ["qkv_proj", "out_proj"]                               | 8039424              | 2.205%     |          |
| 2     | ["qkv_proj", "lm_head"]                                | 8760320              | 2.398%     |          |
| 3     | ["qkv_proj", "out_proj", "lm_head"]                    | 11381760             | 3.094%     |          |
| 4     | ["qkv_proj", "fc_in"]                                  | 11971584             | 3.249%     |          |
| 5     | ["qkv_proj", "fc_out"]                                 | 11971584             | 3.249%     |          |
| 6     | ["qkv_proj", "fc_in", "fc_out"]                        | 18525184             | 4.939%     |          |
| 7     | ["qkv_proj", "out_proj", "lm_head", "fc_in", "fc_out"] | 24488960             | 6.427%     |          |

Table 4.2: Different Possible Target Modules Configurations

We suspect this is primarily due to hardware specification , as GPUs can vectorize operations in Fully connected layers more effectively.

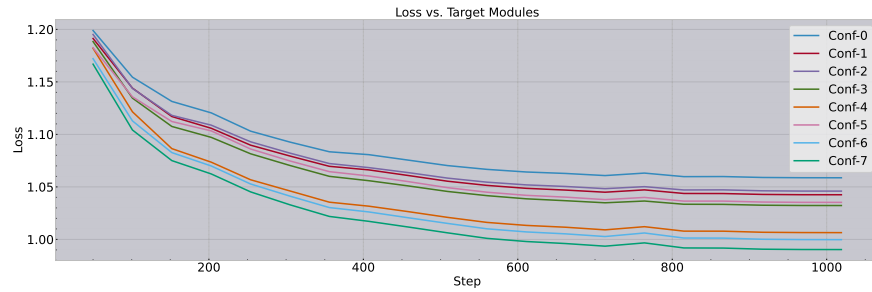


Figure 4.4: Evaluation Loss For Different Target Modules Configurations

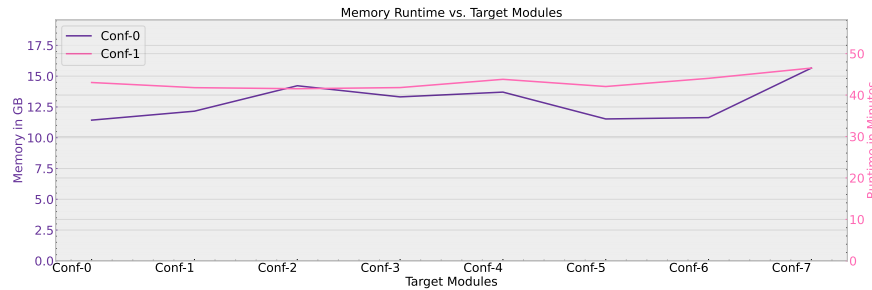


Figure 4.5: Memory and Run-time For Different Target Modules Configurations

**Batch Size** Batch size is a fundamental hyper-parameter that affects the training process by determining the number of samples processed before updating the model's weights. A larger batch size can lead to more stable gradients and potentially faster convergence, but it also requires more memory for processing. We select batch sizes of 1, 2 4, due to resource constraints. Figure 4.6a illustrates the relationship between batch size and evaluation loss. We can observe that smaller batch sizes convergence faster, but larger batch sizes catch up and eventually surpass the smaller ones in terms

of performance. On the efficiency side, Figure 4.6b shows that all batch sizes allocate a maximum of about 14GB during training, this also can be attributed to the fact that GPU memory is allocated in powers of 2. That's way any batch higher than 4 needs to allocate extra blocks of memory and thus exceeding our 15GM limit. The run-time increases proportionally with the batch size.

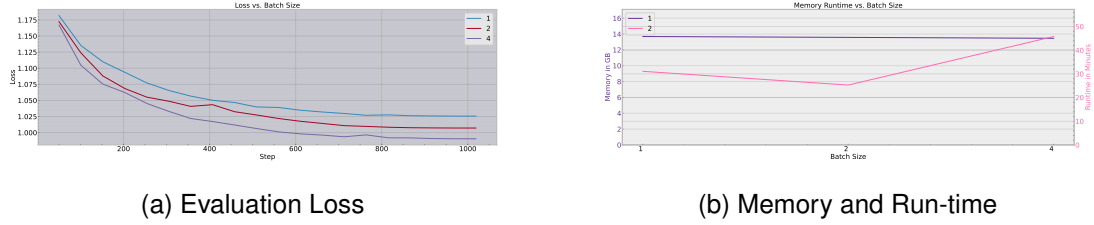


Figure 4.6: Performance and Efficiency For Different Batch sizes

**Sequence Length** refers to the length of input sequences used during training. In the context of code language models, longer sequences might capture more contextual information but also demand more computational resources. To investigate the impact of sequence length on fine-tuning, we experiment with sequence lengths of 128, 256, 512, 1024 and 2048 tokens. As shown in Figure 4.7a, longer sequences lead to improved performance, as they capture more context. Efficiency-wise (Figure 4.7b), shorter sequence lengths are more memory-efficient and require fewer computations, but they sacrifice some performance.

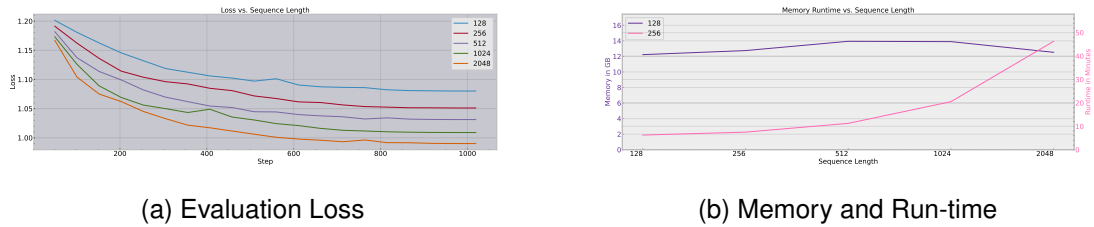


Figure 4.7: Performance and Efficiency For Different Sequence Lengths

**Learning Rate** is a key hyper-parameter that controls the step size during gradient descent. It greatly influences the convergence speed and stability of the training process. We explore learning rates of  $5e-6$ ,  $1e-5$ ,  $5e-5$ , and  $5e-4$ . Figure 4.8a demonstrates the effect of learning rates on evaluation loss. A higher learning rate ( $5e-4$ ) initially leads to faster convergence, but it might become unstable and result in fluctuating performance. On the other hand, lower learning rates ( $5e-6$  and  $1e-5$ ) exhibit slower but steadier convergence. The optimal learning rate seems to be around  $5e-5$  for this experiment.

As for efficiency (Figure 4.8b), the impact of learning rate on memory and time is not substantial compared to other parameters.

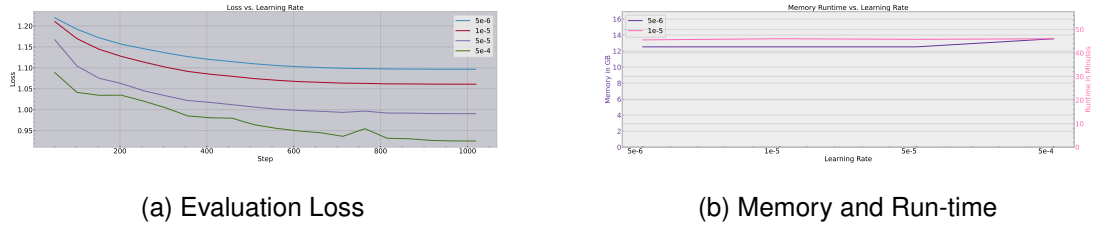


Figure 4.8: Performance and Efficiency For Different Learning Rates

## 4.3 Trade-off Analysis

### 4.3.1 Objective and Setup

The memory and time requirements of the fine-tuning process are two of the most significant drawbacks of fine-tuning code language models. To get good performance on a specific task, one may need to fine-tune larger models with higher GPU memory requirements. A number of studies have also indicated that training for longer periods of time (more steps and epochs) may be advantageous when pre-training large language models[23]. These prerequisites must be met in order to make AI development accessible to everyone.

There are even more intricate variations in the relationship between time, memory, and performance. For example, fine-tuning only a subset of the model's parameters may deliver the same performance as full fine-tuning in a given amount of time. This could be because of the choice of parameters to be fine-tuned [25] or because the smaller model saw a greater number of training tokens in the same time span. On the other hand, slowing the iterations by increasing the batch size could increase the performance, as larger batch sizes are associated with more precise weight updates and better guided learning curves.

In this experiment, we run a trade-off analysis to see if there are any patterns that can help us achieve our goal of making fine-tuning and using code language models more accessible. To imitate real-world conditions, we confine our experiment to a specified memory size and time window. The performance of our baseline model was then measured using the evaluation loss on 50,000 tokens of Java code. We chose a new set of parameters for each fine-tuning run to change the memory allocation and duration

of the process. We will discuss these criteria and provide insights into the obtained outcomes in our analysis.

### 4.3.2 Analysis

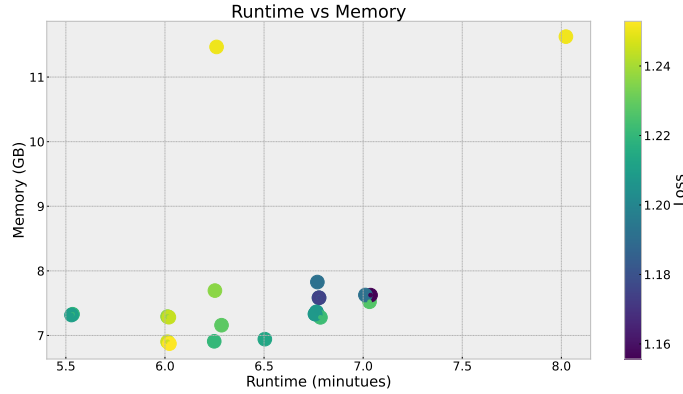


Figure 4.9: Trade Off Analysis

## 4.4 Fine-tuning on Low resource languages

### 4.4.1 Objective and Setup

Large corpora of code crawled from online sources such as GitHub and Stack Overflow are frequently used to train code language models. These datasets typically include a significant number of programming languages, such as TheStack [28], which includes 30 programming languages, and the PolyCoder dataset [53], which includes 12 languages in addition to natural languages. These programming languages, however, are not uniformly distributed in the dataset, as popular languages such as Java and Python typically account for a considerable amount of the data. These variations are typically mirrored in models that have been pre-trained on such datasets, resulting in better performance in popular programming languages and worse performance in low-resource ones.

To overcome this issue, a variety of methods have been offered, including an temperature based sampling of different programming languages [40]. Our methods, on the other hand, take a different approach to overcoming this challenge. We remove the biases in the datasets by utilising monolingual baselines and then training separate

LoRa adapters for each programming language. This also benefits code language model users, as they can simply use an adapter in their unique programming language or easily train and share it. These adapters can also be fine-tuned on a more specialised dataset, such as a Python for Competitive Programming dataset [31].

To test our approach, we fine-tuned our baseline model in four different programming languages: Java, Ruby, Rust, and Swift. As demonstrated in Section 3.2 and Figure 3.3a, these languages were mostly chosen because they represent varying levels of availability in the Stack dataset. We train, test, and share four distinct LoRa adapters using our preprocessed datasets. The following section contains details on the various training parameters as well as a comparison of the results of the evaluation.

#### 4.4.2 Analysis

In this experiment, we fine-tuned our baseline using the same hyper-parameter setup, LoRa configuration, and number of tokens for our four programming languages. Similar to experiments in Section 4.1, we used the CodeGen-Mono baseline with its GPT-2 tokenizer and fine-tuned the model on the processed datasets from Section 3.2. Each model was trained for 10,000 steps, and the training sequence length was 2084 tokens. For the LoRa configuration, we used a rank of 64 with a dropout of 0.05 on the attention, fully connected, and language model head modules. Optimisation was done using the Adam optimizer with a  $5e-5$  learning rate, 100-step warm-up, and cosine weight decay. We used a batch size of 4 with no gradient accumulation. Gradient check-pointing was used for efficiency along with 16-bit training.

The results in Figure 4.10 show the loss on the evaluation split every 50 steps for each model. We notice that all the models follow a similar trajectory. The loss falls sharply in the early steps, and as the training progresses, the graphs flatten, indicating convergence. However, there are a few noteworthy artefacts upon closer examination of the graphs and the training data. The first observation is that the Java loss curve starts significantly lower when compared to all other models. We hypothesise that this is related to the fact that the Baseline model has already seen Java code in its pretraining due to the data leakage described in exp1. The code in Figure 2 shows an example of Java code inside a Python file, which is more common than seeing other language leaks due to the sheer popularity of Java. The second observation is concerning the Ruby model. We notice that the loss converges at a higher value compared to the other programming languages. That is due to the fact that Ruby shares a lot of similarities

with Python as they both use indentation instead of braces, are dynamically typed, and share a number of keywords. These similarities confuses the model as it frequently generates Python code instead of Ruby, as we will show in the error analysis section. The work of [10] reported similar observations in the task of code translation.

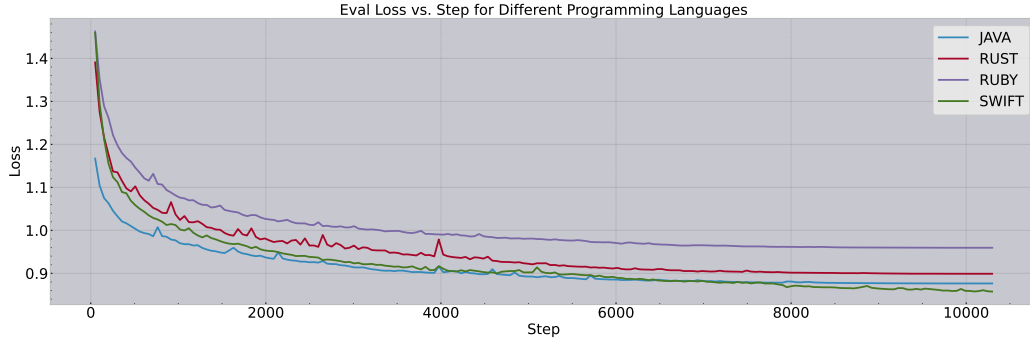


Figure 4.10: Evaluation Loss For Target Programming Languages

## 4.5 Error Analysis

### 4.5.1 Objective and Setup

In our final experiment, we conducted error analysis on our fine-tuned models in order to better understand and obtain insights into their performance. We investigate the code produced by efficiently fine-tuned models, fully fine-tuned models, and both monolingual and multilingual baseline models. The code is generated as responses to prompts in different programming languages, taken from our evaluation dataset [14]. We make an effort to identify any systematic errors exhibited by the models that reveal the shortcomings of our approach. We additionally follow [11]’s work and categorise some of the prompts depending on their type and level of difficulty. This knowledge will enable us to develop the models in the future and identify the most effective uses for them now.

### 4.5.2 Analysis

| Category                    | Theme  | Example   |
|-----------------------------|--|---|
| Highest Performing Problems | Single operations                            | <pre>def sum_to_n(n: int) -&gt; int:     """sum_to_n is a function that sums numbers from 1 to n. 3 """</pre>   |
|                             | Common type questions                        | <pre>def fib(n: int) -&gt; int:     """Return n-th Fibonacci number. """</pre>  |
| Lowest Performing Problems  | Problems with multiple subproblems           | <pre>def separate_paren_groups(paren_string: str) -&gt; List[str]:     """ Input to this function is a string containing multiple groups of nested parentheses. Your goal is to     separate those group into separate strings and return the list of those. Separate groups are balanced     (each open brace is properly closed) and not nested within each other Ignore any spaces in the input string. """     (Sub-Problems: Remove Spaces, Identify Parentheses Groups, Balanced Parentheses Checking, Extract Substrings, Combine Results)</pre> |
|                             | Solving a more common version of the problem | <pre>def intersperse(numbers: List[int], delimiter: int) -&gt; List[int]:     """ Insert a number 'delimiter' between every two consecutive elements of input list 'numbers' """     return list(map(lambda x: x if x % 2 == 0 else x + delimiter, numbers))     (the model try to insert the delimiter between even elements instead of every two consecutive elements)</pre>  |
|                             | Miscellaneous errors                         | <pre>def parse_music(music_string: str) -&gt; List[int]:     """ Input to this function is a string representing musical notes in a special ASCII format. Your task is     to parse this string and return list of integers corresponding to how many beats does each not last. Here is a legend:     'o' - whole note, lasts four beats     'o—' - half note, lasts two beats     'o—' - quater note, lasts one beat     parse_music('o o— o— o— o— o o') &gt;&gt;&gt; [4, 2, 1, 2, 2, 1, 1, 1, 4, 4] """     (Specialized Problem)</pre>              |

Table 4.3



# Chapter 5

## Conclusions

**Edit: add ways forward + considerations** *The journey towards democratizing the field of artificial intelligence and code language models is a multifaceted endeavor that requires addressing challenges on various fronts. This work has presented a concerted effort to bridge the gap between advanced AI technologies and their practical usability, particularly in the domain of code intelligence. By focusing on accessibility, usability, and empirical understanding, we have contributed to the ongoing narrative of democratization in AI. Through the extension of a mono-lingual code LLM to encompass multiple programming languages, we have demonstrated the potential of these models to transcend language barriers and empower developers across diverse linguistic landscapes. Our decision to openly share the fine-tuned models, datasets, and evaluation results aligns with the ethos of democratization, fostering collaborative research and enabling the broader community to benefit from these advancements. The empirical insights gained through extensive experimentation shed light on the intricacies of fine-tuning code LLMs. These insights equip practitioners with valuable knowledge, helping them navigate the complexities of model training, saving resources, and ultimately driving innovation more effectively. Furthermore, the discussions around AI democratization provide a holistic perspective on the challenges and opportunities inherent in the process, urging us all to prioritize inclusivity and ethical considerations in AI development. As we look ahead, the continued effort to democratize AI necessitates ongoing collaboration, iterative improvements, and sustained community engagement. The expansion of accessible code language models, coupled with empirical evidence and shared resources, empowers practitioners to harness the potential of AI in software development, education, and beyond. By embracing this path, we contribute to a future where AI technologies are harnessed by a wider array of individuals, ultimately leading*

*to more equitable technological advancements. In closing, the strides made in this work are part of a larger movement towards democratizing AI, with the aim of ensuring that the benefits of advanced technology are accessible to all. As the field evolves, embracing open collaboration, transparency, and usability will be critical in realizing the full potential of AI for the betterment of society.*

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# **Appendix A**

## **First appendix**

### **A.1 First section**

Any appendices, including any required ethics information, should be included after the references.

Markers do not have to consider appendices. Make sure that your contributions are made clear in the main body of the dissertation (within the page limit).

# **Appendix B**

## **Participants' information sheet**

If you had human participants, include key information that they were given in an appendix, and point to it from the ethics declaration.

## **Appendix C**

### **Participants' consent form**

If you had human participants, include information about how consent was gathered in an appendix, and point to it from the ethics declaration.