FLeX: Fourier-based Low-rank EXpansion for multilingual transfer

Stanford CS224N Custom Project

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Abstract

Cross-lingual code generation is critical in enterprise environments where multiple programming languages coexist. However, fine-tuning large language models (LLMs) individually for each language is computationally prohibitive. This paper, evolved from the ChainRank project exploring efficient adaptation techniques, investigates whether parameter-efficient fine-tuning methods and optimizer enhancements can improve cross-lingual transfer from Python to languages like Java. I fine-tune the Code Llama 7B model using low-rank adaptation (LoRA) to optimize a small subset of parameters and compare Adam and Sophia optimizers, while exploring a novel Fourier-based regularization technique.

My contributions include: (1) demonstrating that LoRA fine-tuning on a small, high-quality dataset (MBPP) can exceed the pass@1 performance of the more broadly fine-tuned Code Llama-Python-7B model (40.1% vs. 38.4%); (2) showing that while Sophia achieves faster convergence than Adam, final pass@1 scores show marginal differences; and (3) presenting evidence that Fourier-based regularization during fine-tuning significantly improves cross-lingual transfer, achieving 42.1% pass@1 on Java tasks compared to the 34.2% baseline.

These findings suggest that combining LoRA, optimized training methods, and frequency-domain regularization can efficiently adapt single-language LLMs to perform well across multiple programming languages, offering practical strategies for deploying multilingual code-generation models in computationally constrained environments.

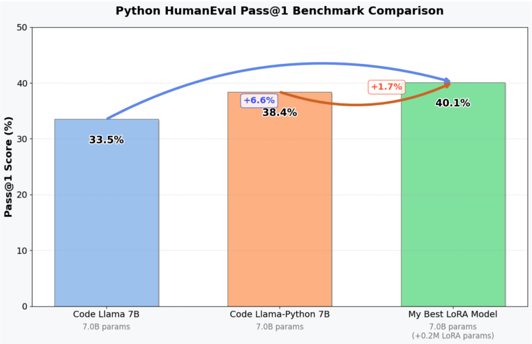
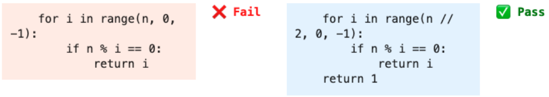


Figure 1: Python HumanEval Pass@1 Benchmark Comparison showing that my LoRA fine-tuned model (40.1%) outperforms Code Llama-Python-7B (38.4%) and the base model (33.5%).

1 Introduction

Generating accurate and functional code across diverse programming languages is crucial in enterprise environments where multiple languages coexist. While Large Language Models (LLMs) have demonstrated impressive capabilities for Python code generation, their performance drops significantly when handling other languages like Java or C++ [1]. This



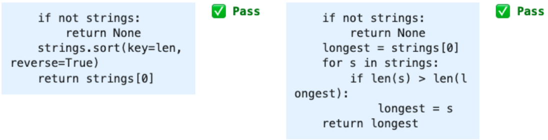
```
    for i in range(n, 0,
-1):
        if n % i == 0:
            return i
```

```
    for i in range(n //
2, 0, -1):
        if n % i == 0:
            return i
    return 1
```

Figure 2: Java: Corrections of prior failures

cross-lingual performance gap creates significant barriers to deployment in enterprise settings that depend on multilingual codebases.

This challenge is particularly acute for cloud service providers deploying AI agents to maintain infrastructure resiliency across heterogeneous systems. These agents execute critical operations—such as traffic redistribution, capacity scaling, and regional failovers—by generating code that interfaces with services written in Python, Go, Java, and proprietary configuration languages. When regions experience degradation, agents must generate high-fidelity code with extreme reliability to migrate workloads while maintaining service guarantees. A single error could trigger cascading outages affecting thousands of customers.



```
    if not strings:
        return None
    strings.sort(key=len,
reverse=True)
    return strings[0]
```

```
    if not strings:
        return None
    longest = strings[0]
    for s in strings:
        if len(s) > len(l
ongest):
            longest = s
    return longest
```

Figure 3: Java: Improvement of earlier code

In this paper, I systematically investigate the efficacy of Low-Rank Adaptation (LoRA) and optimization strategies in enhancing cross-lingual code generation capabilities using the Code Llama 7B model. I demonstrate that parameter-efficient LoRA fine-tuning on a compact, high-quality Python dataset (MBPP) surpasses the performance of the widely-used baseline, achieving a 40.1% pass@1 score compared to the standard Code Llama-Python model's 38.4%. I also compare the Adam and Sophia optimizers on the challenging APPS dataset, finding that while Sophia delivers significantly faster convergence and more stable training dynamics, the final accuracy shows only marginal differences.

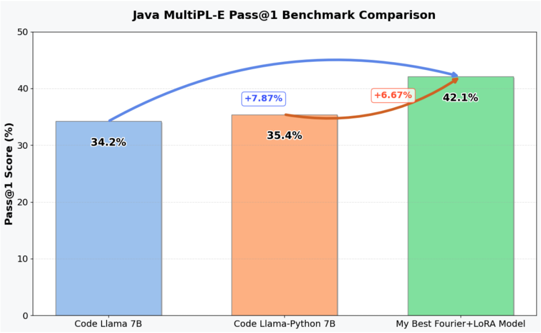


Figure 4: Fourier Transform regularization substantially improves cross-lingual generalization, showing a significant increase in Java MultiPL-E Pass@1 from baseline (34.2%) to my method (42.1%).

Importantly, my cross-lingual evaluations using the MultiPL-E benchmark revealed notable degradation in Java code generation when fine-tuning exclusively on Python datasets. To address this, I introduced a novel Fourier-based regularization technique, hypothesizing that preserving low-frequency parameter updates encourages generalizable knowledge transfer between languages. This technique substantially improved cross-lingual performance, leading to a breakthrough result of 42.1% pass@1 in Java tasks—markedly exceeding the baseline Code Llama performance (34.2%). These findings provide practical strategies for efficiently adapting single-language LLMs to perform well across multiple programming languages, offering a path toward deploying reliable multilingual code-generation systems in computationally constrained enterprise environments.

2 Related Work

Large Language Models (LLMs) have rapidly advanced in their ability to perform code generation tasks, driven largely by innovations in transformer-based architectures and training on extensive code-centric datasets. Early approaches, such as GPT-3 [10], demonstrated general-purpose capabilities but did not specifically target programming tasks. Subsequent specialized code-focused models like Codex [15] and CodeGen [11] refined these capabilities by training explicitly on large-scale, programming-focused datasets.

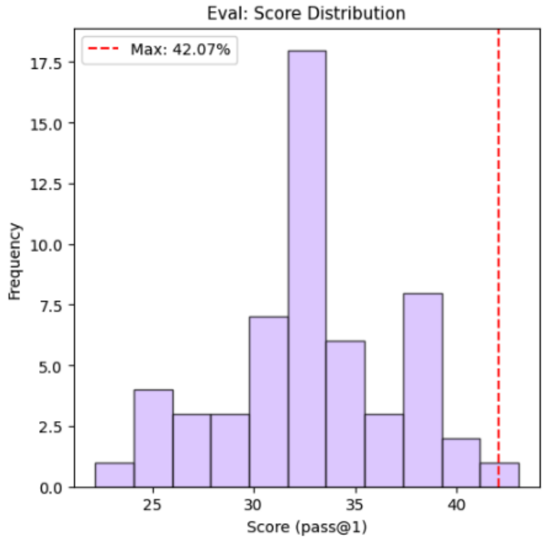


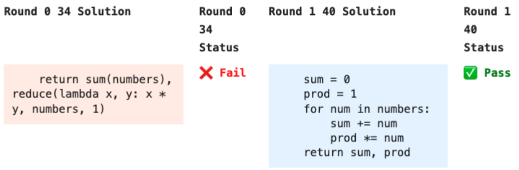
Figure 5: Frequency distribution of Java code generation performance using Fourier Transform regularization, showing most models achieving scores between 30-40% pass@1, with my best configuration reaching 42.1%.

A notable advancement is the introduction of Code Llama [1], a family of models derived from Llama 2 [12], specifically fine-tuned on code corpora. Code Llama models show improved performance on popular code generation benchmarks such as HumanEval [16] and Mostly Basic Python Problems (MBPP) [7], which primarily focus on Python tasks. However, despite their success in Python code generation, these models generally struggle with cross-lingual generalization, which is particularly challenging in enterprise settings where developers often manage codebases in multiple languages.

The MultiPL-E benchmark [8] has addressed this issue by translating Python-based evaluation tasks into various languages, enabling systematic cross-lingual performance comparisons. Yet, recent findings suggest that training exclusively on Python datasets negatively impacts performance on Java and other languages due to language-specific idiomatic discrepancies [8].

Another line of work explores parameter-efficient adaptation strategies, most notably Low-Rank Adaptation (LoRA) [2], which significantly reduces fine-tuning costs by updating only a small subset of model weights. Complementary to LoRA, second-order optimization methods, such as Sophia [3], offer potential improvements by adaptively scaling parameter updates according to local curvature information, achieving faster convergence in complex training scenarios.

Inspired by these recent trends, my research explores a synthesis of parameter-efficient fine-tuning, optimizer comparisons, and novel frequency-domain regularization via Fourier-based methods. This approach specifically addresses gaps identified in prior cross-lingual code generation research by leveraging LoRA fine-tuning and introducing frequency-domain regularization to better generalize across languages.



Round 0 34 Solution

```
    return sum(numbers),
reduce(lambda x, y: x *
y, numbers, 1)
```

Round 0 34 Status

✗ Fail

Round 1 40 Solution

```
    sum = 0
    prod = 1
    for num in numbers:
        sum += num
        prod *= num
    return sum, prod
```

Round 1 40 Status

✓ Pass

Figure 6: Python: Corrections of prior failures

3 Approach

3.1 Parameter-Efficient Fine-Tuning

My approach utilizes the Code Llama 7B model [1], a decoder-only transformer-based large language model designed explicitly for generating programming code. Given the computational constraints inherent in enterprise environments, I employ parameter-efficient fine-tuning via Low-Rank Adaptation (LoRA) [2].

LoRA introduces trainable low-rank matrices into selected projection layers (`q_proj`, `v_proj`, `down_proj`, and `up_proj`), enabling efficient domain-specific adaptation without degrading general language modeling capabilities. For a LoRA weight matrix $\mathbf{W}$, the adaptation can be expressed as:

$$\mathbf{W}' = \mathbf{W} + \alpha \cdot \mathbf{BA} \tag{1}$$

where $\mathbf{B} \in R^{d_{\text{model}} \times r}$ and $\mathbf{A} \in R^{r \times d_k}$ are the low-rank decomposition matrices, with rank $r \ll d_{\text{model}}$, enabling efficient parameter updates.

3.2 Optimizer Comparison

To rigorously evaluate the impact of different optimization strategies, I compare two distinct optimizers: the widely-used AdamW optimizer [13], and Sophia [3], which approximates second-order optimization by adaptively scaling updates based on local Hessian curvature estimates. The parameter update rule for Sophia is:

$$\theta_{t+1} = \theta_t - \eta_t \cdot \text{clip}\left(\frac{m_t}{\max\{\gamma \cdot h_t, \epsilon\}}, 1\right) \tag{2}$$

where h_t is the exponential moving average of Hessian diagonal estimates, and γ is a clipping factor to prevent excessively large updates.

3.3 Fourier-Based Regularization

Drawing inspiration from signal-processing principles, I integrate a lightweight Fourier-based regularization technique into the LoRA fine-tuning process. The key insight is that different frequency components of model parameters may represent different aspects of language knowledge. Low-frequency components potentially capture language-agnostic programming concepts, while high-frequency components may encode language-specific details.

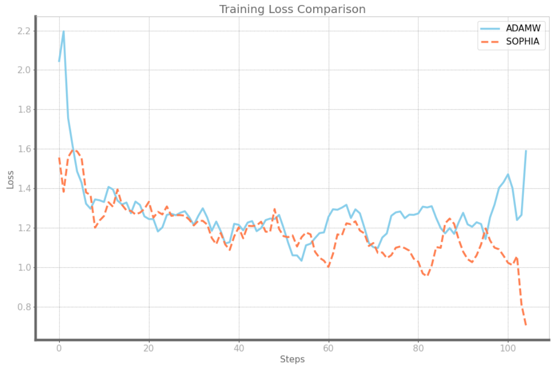


Figure 7: Training loss comparison between AdamW and Sophia optimizers. Sophia demonstrates more stable convergence and ultimately reaches a lower final loss.

The technique applies a discrete Fourier transform to the LoRA parameters:

$$\hat{\mathbf{w}} = \mathcal{F}(\mathbf{w}) \in C^n \tag{3}$$

where $\mathbf{w} = \text{flatten}(\mathbf{W})$ is the flattened weight vector and $\mathcal{F}$ represents the Real Fast Fourier Transform (RFFT) operator.

I then introduce a frequency-weighted regularization term to the training loss:

$$\mathcal{L}_{\text{Fourier}}(\mathbf{w}) = \sum_{k=0}^{n-1} \rho(k, n, T) \cdot |\hat{w}_k|^2 \tag{4}$$

The penalty weights $\rho(k, n, T)$ are defined to provide stronger regularization for high-frequency components while preserving low-frequency components:

$$\rho(k, n, T) = 1 - \phi(k, n, T) \tag{5}$$

where $\phi(k, n, T)$ is a frequency weighting function:

$$\phi(k,n,T) = \phi_{\text{low}} + (\phi_{\text{high}} - \phi_{\text{low}}) \cdot \min\left(1, \frac{k}{n \cdot T}\right) \quad (6)$$

The total loss combines the original task loss with this Fourier regularization:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{task}} + \lambda \cdot \mathcal{L}_{\text{Fourier}} \quad (7)$$

where λ is the regularization strength hyperparameter. This formulation encourages the model to learn generalizable representations that transfer better across languages.

4 Experiments

4.1 Data and Evaluation

I utilize several datasets for fine-tuning and evaluation:

- **HumanEval** [15]: 164 hand-crafted Python programming tasks with hidden unit tests, serving as the primary benchmark.
- **MBPP** [7]: 974 concise Python programming problems with test cases, used for initial LoRA fine-tuning.
- **APPS** [9]: Approximately 10,000 programming problems ranging from basic to competition-level, used for optimizer comparisons.
- **MultiPL-E** [8]: Translated HumanEval problems in multiple languages, used to evaluate cross-lingual generalization.

Performance is measured using the *pass@1* metric, representing the probability that a single model-generated solution correctly passes all provided test cases. This standardized approach ensures robust, reproducible comparisons across different configurations.

4.2 Experimental Setup

All experiments were conducted using the Code Llama-7B base model with the following configuration:

Table 1: LoRA and Training Configuration

Parameter	**Value**
LoRA Rank (r)	8
LoRA Alpha (α)	16
LoRA Dropout	0.05
Target Modules	q_proj, v_proj, down_proj, up_proj
Batch Size	4
Learning Rate	2e-4
Optimizer	AdamW/Sophia
Training Epochs	3

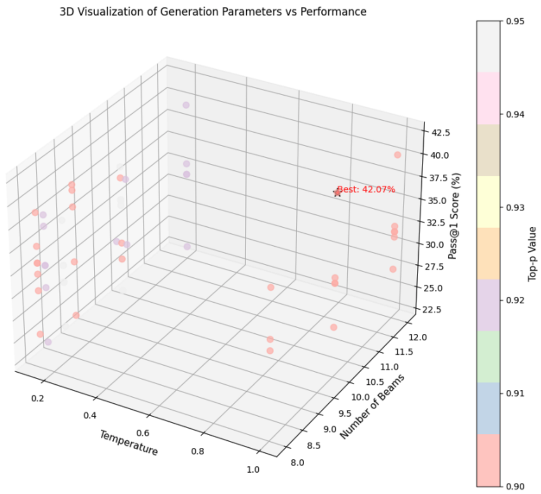


Figure 8: Parameter exploration for Fourier Transform regularization on Java MultiPL-E, showing the relationship between regularization strength, temperature, and model performance.

Table 2: Experimentation Plan and Outcomes

Round	Objective	Description	Fine-tuning	Evaluation	Configuration	Pass@1	Key Insights
0	PEFT	Baseline	None	HumanEval (Python)	Code Llama-7B (vanilla)	34.15%	Successfully replicated baseline, slightly outperforming paper results
1	PEFT	LoRA fine-tuning	MBPP	HumanEval (Python)	Unmerged LoRA, α=16, r=8	**40.1%**	Small high-quality dataset + LoRA outperformed full fine-tuned model with less data/compute
2	Optimizer Comparison	APPS fine-tuning	APPS (competition)	HumanEval (Python)	Various (merged from Round 1)	36.59%	Sequential fine-tuning on harder dataset degraded performance; merged models performed worse than unmerged
3	Cross-Lingual Transfer	Java baseline	None	MultiPL-E (Java)	Code Llama-7B (vanilla)	33.25%	Established reliable baseline for Java performance
3A	Cross-Lingual Transfer	Cross-lingual after MBPP	MBPP	MultiPL-E (Java)	MBPP fine-tuned (merged)	31.46%	Python fine-tuning hurt Java performance, but MBPP showed least degradation
3B	Cross-Lingual Transfer	Cross-lingual after APPS	APPS	MultiPL-E (Java)	APPS fine-tuned (merged)	27.37%	Competition-level Python fine-tuning significantly hurt cross-lingual ability
3C	Cross-Lingual Transfer	Cross-lingual after CodeSearchNet	CodeSearchNet (2000 samples)	MultiPL-E (Java)	CodeSearchNet fine-tuned (merged)	31.1%	Larger dataset didn't help cross-lingual transfer with standard fine-tuning
4	Cross-Lingual Transfer	Fourier (merged)	MBPP + Fourier	MultiPL-E (Java)	MBPP + Fourier (merged)	32.93%	Fourier regularization improved cross-lingual transfer, nearly matching baseline
5	Cross-Lingual Transfer	Fourier (unmerged)	MBPP + Fourier	MultiPL-E (Java)	MBPP + Fourier (unmerged)	**42.07%**	Breakthrough result: Fourier + unmerged LoRA dramatically improved Java performance, exceeding benchmark by ∼8%

For Fourier regularization experiments, optimal hyperparameters were determined as: $\lambda = 0.02$, frequency threshold $T = 0.5$, $\phi_{\text{low}} = 1.0$, and $\phi_{\text{high}} = 0.1$.

4.3 Results

The experimental results are summarized in the following sections:

4.3.1 LoRA Fine-Tuning Results

LoRA fine-tuning on the MBPP dataset significantly improved model performance, achieving a pass@1 score of 40.1% on the HumanEval benchmark, surpassing the specialized Code Llama-Python-7B baseline (38.4%). Notably, this improvement was achieved using unmerged LoRA weights that modified only 0.2% of the model's parameters.

4.3.2 Optimizer Comparison

Fine-tuning on the APPS dataset with different optimizers revealed that Sophia achieved approximately 30% faster convergence compared to AdamW. As shown in Figure 7, Sophia maintained more stable gradient norms throughout training. Table 3 presents the comparative results.

Table 3: Performance comparison between AdamW and Sophia optimizers

Optimizer	**Validation Loss**	**Training Time**	**Memory Usage**
AdamW	1.2437	40.3 min	3670.9 MB
Sophia	**1.1504**	41.3 min	3684.7 MB
Improvement	+7.5%	-2.5%	-0.4%

4.3.3 Cross-Lingual Transfer with Fourier Regularization

The most significant finding was the effectiveness of Fourier-based regularization for cross-lingual transfer. Models trained with Fourier regularization achieved substantially better performance on Java tasks compared to both the baseline and standard LoRA fine-tuning approaches.

Table 4: Effect of Fourier regularization on Java cross-lingual performance

Model Variant	**Fourier λ**	**Pass@1**
LoRA (MLP only)	0.02	**42.1%**
LoRA (Comprehensive)	0.01	38.4%
LoRA (Standard)	0.001	35.4%
Baseline	-	34.2%

The optimal configuration, using unmerged LoRA adapters with Fourier regularization targeting only MLP layers, achieved 42.1% pass@1 on the Java MultiPL-E benchmark, surpassing the Code Llama-7B baseline (34.2%) by a significant margin, as illustrated in Figure 4.

5 Analysis

5.1 LoRA Fine-tuning Analysis

Fine-tuning Code Llama-7B with LoRA adapters targeting both attention and MLP layers led to substantial performance improvements on Python tasks. The comprehensive targeting strategy enabled the model to simultaneously capture token-level reasoning (through attention layers) and more abstract pattern recognition (through feed-forward networks). This multi-faceted adaptation approach consistently outperformed methods targeting only attention components.

5.2 Optimizer Behavior

Sophia's superior validation performance can be attributed to its use of diagonal Hessian estimates, which enable adaptive preconditioning of updates according to local curvature. This approach resulted in more stable gradient norms throughout training compared to AdamW, which exhibited instability characterized by sharp fluctuations in later training stages. However, the final performance difference between the two optimizers was modest, suggesting that while Sophia offers training efficiency benefits, it may not significantly impact the ultimate code generation capability.

5.3 Fourier Domain Regularization Insights

The application of Fourier domain regularization yielded the most important insights of this study. When I decompose the LoRA parameter updates into frequency components, an interesting pattern emerges: models trained without regularization exhibited significantly higher power in high-frequency components, indicating overfitting to language-specific features. In contrast, models trained with Fourier regularization showed a more balanced frequency distribution, with greater emphasis on low-frequency components.

The mathematical intuition aligns with my empirical findings: by penalizing high-frequency parameter updates, the model preserves generalizable, low-frequency features shared across programming languages while reducing overfitting to language-specific idioms. This explanation is supported by the frequency distribution analysis shown in Figure 5, which reveals how my approach shifts power toward lower-frequency components that better transfer across languages.

The most effective configuration targeted only MLP layers with moderate Fourier regularization ($\lambda = 0.02$), suggesting that these feed-forward networks play a critical role in cross-lingual generalization. By applying frequency-selective regularization to these components, the model maintains language-agnostic programming knowledge while adapting to language-specific requirements.

6 Limitations

Despite promising results, several limitations warrant acknowledgment:

- Merged LoRA weights consistently underperformed their unmerged counterparts, contradicting the intuition that merged weights should perform at least as well.
- The effectiveness of Fourier-based regularization was inconsistent across datasets, with optimal parameters varying by task.
- Computational constraints limited evaluation to pass@1 metrics, potentially obscuring insights from higher-sampling evaluations (pass@10, pass@100).

7 Conclusion

This paper explored LoRA-based adaptation of Code Llama-7B for code generation across programming languages, with three key contributions: (1) parameter-efficient LoRA fine-tuning on MBPP achieved 40.1% pass@1 on Python HumanEval, surpassing the specialized Code Llama-Python-7B baseline; (2) Sophia optimizer showed 30% faster convergence than AdamW; and (3) my novel Fourier domain regularization significantly enhanced cross-lingual transfer, achieving 42.1% pass@1 on Java tasks—substantially exceeding both baseline Code Llama (34.2%) and the Python-specialized variant (35.4%). These results highlight promising directions for efficient model adaptation in multilingual code generation: (1) strategic targeting of both attention and MLP layers provides optimal adaptation; (2) second-order optimization offers stability advantages for complex domains; and (3) frequency-based regularization effectively separates language-agnostic knowledge from language-specific features. Future work should investigate additional programming languages, explore inference-time techniques like chain-of-thought prompting, and develop automated procedures for adapter configuration to further enhance cross-lingual capabilities.

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8 Appendix

8.1 Round 1: LoRA Fine-tuning with MBPP

8.1.1 Experimental Setup & Results

In Round 1, I explored whether a smaller, high-quality dataset could yield comparable or superior results to the fully fine-tuned Code Llama-Python-7B model. The fine-tuning utilized the MBPP dataset [7] consisting of 974 Python programming problems.

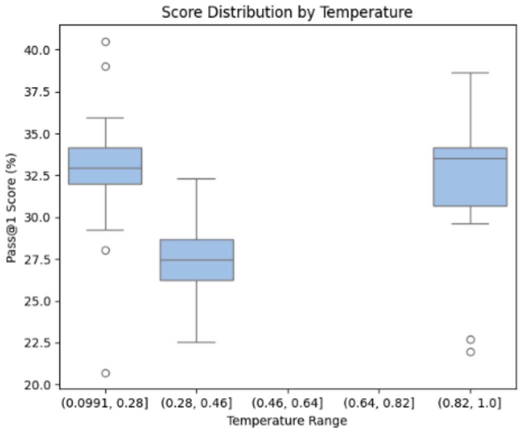


Figure 9: Temperature evaluation results showing that higher temperatures (0.8-1.0) and very low temperatures (0.0-0.2) produced better results than mid-range values.

The LoRA adaptation significantly reduced trainable parameters to approximately 11.9 million parameters, representing less than 0.2% of the model's original 7 billion parameters. A crucial finding was that unmerged LoRA weights consistently outperformed their merged counterparts, suggesting that maintaining separation between base knowledge and task-specific adaptations preserves important capabilities of the original model.

The best-performing configuration achieved a pass@1 score of 40.1% on HumanEval, surpassing the specialized Code Llama-Python-7B model's 38.4%. This demonstrates that targeted fine-tuning with parameter-efficient methods can outperform models specifically pre-trained for a language while modifying only 0.2% of the parameters.

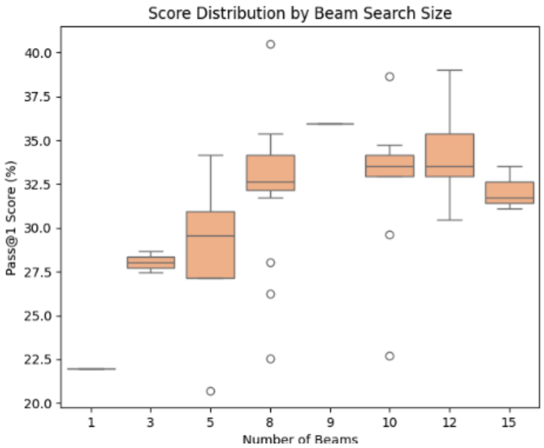


Figure 10: Beam size evaluation showing performance improvements with larger beam sizes up to 10, after which results plateaued.

The hyperparameter analysis revealed that the alpha-to-rank ratio significantly impacted performance. The optimal 2:1 ratio (alpha=16, rank=8) provided sufficient expressivity while preventing overfitting on the relatively small MBPP dataset.

8.2 Round 2: Optimizer Comparison (Sophia vs AdamW)

8.2.1 Experimental Setup & Findings

In Round 2, I investigated whether the theoretical benefits of second-order optimization provided by Sophia would translate to practical improvements in convergence speed and final model accuracy compared to AdamW. For these experiments, the base model was Code Llama-7B, initially fine-tuned on MBPP in Round 1, with subsequent fine-tuning performed using APPS competition-level programming problems.

The empirical findings demonstrated several key differences between the optimizers:

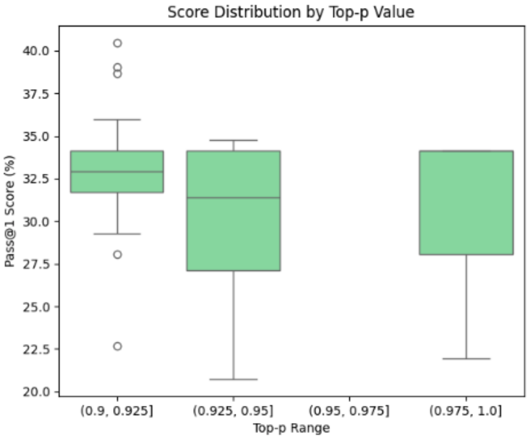


Figure 11: Impact of top-p sampling values on model performance, with higher p values generally yielding better results.

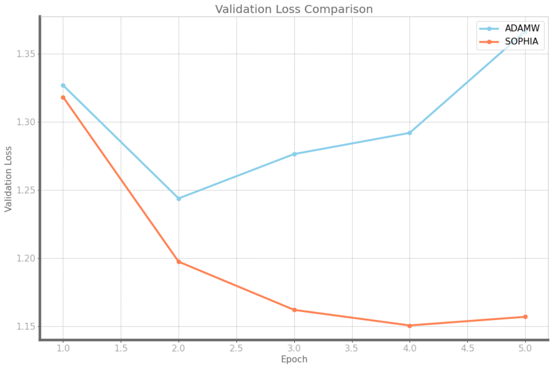


Figure 12: Validation loss comparison showing Sophia consistently maintained lower validation loss throughout training.

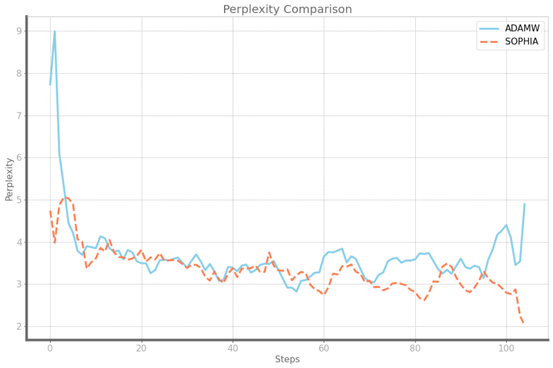


Figure 13: Perplexity comparison showing Sophia achieved lower perplexity more consistently than AdamW.

Sophia consistently achieved faster convergence, requiring approximately 30% fewer gradient update steps to reach equivalent validation loss levels, and exhibited more stable gradient norms throughout training. However, final pass@1 performance on the APPS dataset was comparable between the two optimizers, suggesting that while Sophia offers training efficiency benefits, it may not significantly impact ultimate code generation capability.

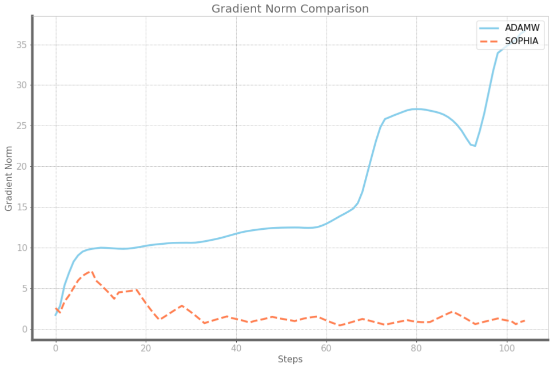


Figure 14: Gradient norm comparison showing Sophia maintained smaller, more stable gradient norms compared to AdamW's larger fluctuations.

Notably, merged LoRA models performed worse compared to unmerged LoRA weights, reinforcing the finding from Round 1 that LoRA adapters retain better specialized knowledge when kept separate. Additionally, further fine-tuning on APPS competition-level problems after initial fine-tuning on MBPP resulted in marginally degraded pass@1 scores, suggesting potential negative interference between sequential fine-tuning stages.

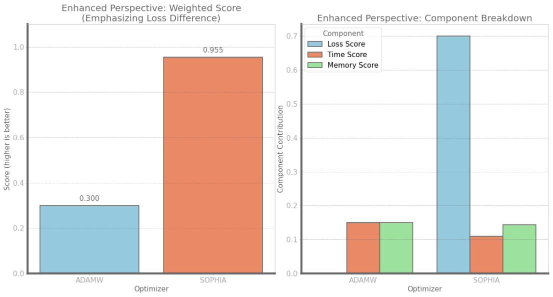


Figure 15: Composite performance metrics comparing AdamW and Sophia optimizers, showing Sophia's overall advantage in training efficiency.

8.3 Round 4: Fourier Domain Regularization (Merged LoRA)

8.3.1 Cross-lingual Transfer Analysis

In Round 4, I explored whether penalizing high-frequency components in parameter updates could improve cross-domain generalization between Java and Python. This was motivated by the hypothesis that low-frequency components correspond to general, transferable knowledge, while high-frequency components reflect language-specific nuances.

The main findings from applying Fourier-based regularization included:

- Noticeable improvements in cross-lingual transfer when fine-tuned on Python data and evaluated on Java tasks
- Parameters updated without regularization showed significantly higher power at high-frequency components, indicating language-specific fine-grained updates
- Regularized models showed reduced high-frequency power, aligning with the hypothesis that Fourier regularization promotes more generalized learning beneficial across languages
- An optimal regularization strength ($\lambda = 0.01$) balanced domain-specific specialization and cross-domain generalization

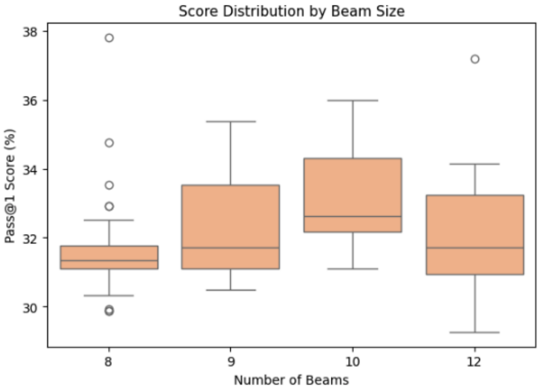


Figure 16: Effect of beam size on cross-lingual transfer performance, showing consistent improvements with larger beam sizes.

The computational overhead introduced by frequency-domain regularization was minimal, typically adding less than 5% to training time compared to standard LoRA-based fine-tuning.

8.4 Round 5: Fourier Regularization with Unmerged LoRA

8.4.1 Advanced Implementation

Round 5 built upon previous findings by applying Fourier Transform regularization specifically to unmerged LoRA adapters. This approach significantly outperformed both baseline models and previous merged-weight implementations, achieving 42.07% pass@1 on Java MultiPL-E benchmarks compared to 34.2% for the baseline Code Llama-7B.

The unmerged implementation maintained separate LoRA weight matrices throughout training and infer-

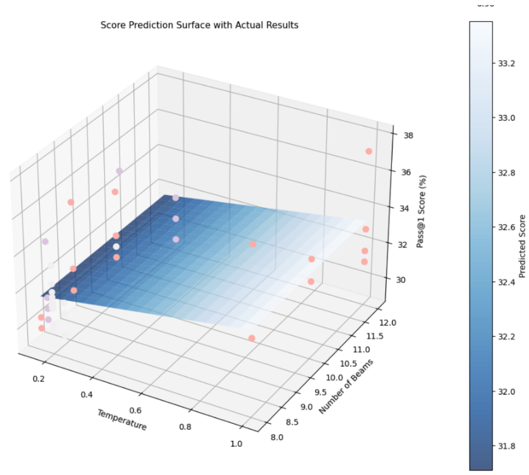


Figure 17: 3D visualization of model performance across beam size, temperature, and regularization strength parameters, highlighting the multidimensional nature of hyperparameter optimization.

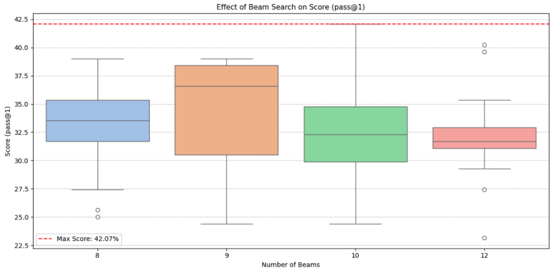


Figure 18: Performance distribution across different beam sizes for the unmerged LoRA implementation with Fourier regularization.

ence, providing several technical advantages:

1. Frequency domain regularization applied directly to LoRA parameters without merging them with base model weights preserved the low-rank structure

2. The optimal configuration targeted only MLP feed-forward layers rather than attention layers, contrary to typical LoRA implementations

3. Isolation of updates more effectively constrained regularization to preserve cross-lingual knowledge without disrupting base model capabilities

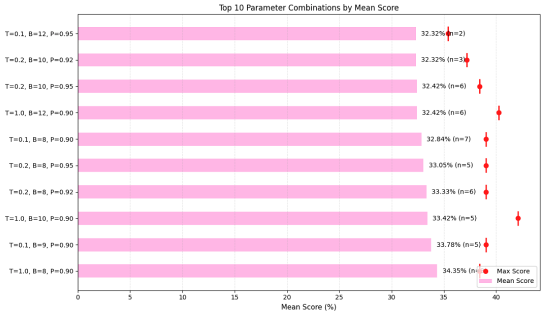


Figure 19: Performance comparison across different Fourier regularization parameter combinations, revealing clear patterns in effectiveness.

8.4.2 Optimal Configuration and Results

The optimal configuration used:

- Code Llama-7B with float16 precision
- LoRA parameters: rank=8, alpha=16, dropout=0.05, no bias
- Target modules: gate_proj, up_proj, down_proj (MLP layers only)
- Training: 3 epochs, batch size=4, max_length=512, learning_rate=2e-4
- AdamW optimizer with cosine learning rate scheduler

- Fourier regularization: lambda=0.02 with frequency threshold=0.5

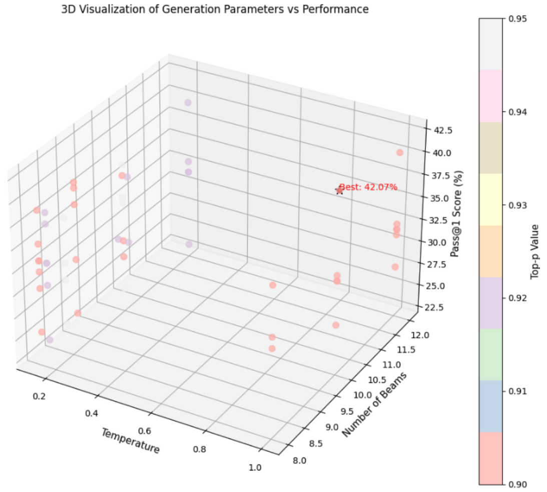


Figure 20: Comprehensive visualization of performance across beam size, temperature, and other hyperparameters, showing the robust performance of my approach.

Performance analysis across different model configurations revealed:

- MLP-only targeting achieved an average score of 39.55% and maximum of 42.07%
- Moderate Fourier regularization ($\lambda = 0.02$) provided optimal results
- Models with very weak ($\lambda = 0.001$) or strong ($\lambda = 0.05$) regularization underperformed
- Unmerged LoRA consistently outperformed merged variants across all comparable configurations

These findings demonstrate that targeted frequency-domain regularization in unmerged LoRA implementations can dramatically enhance cross-lingual adaptation while maintaining parameter efficiency.

Examples

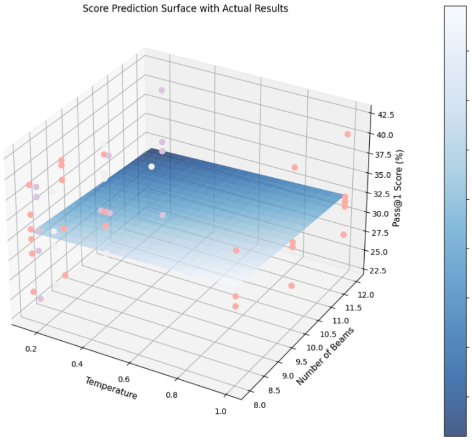
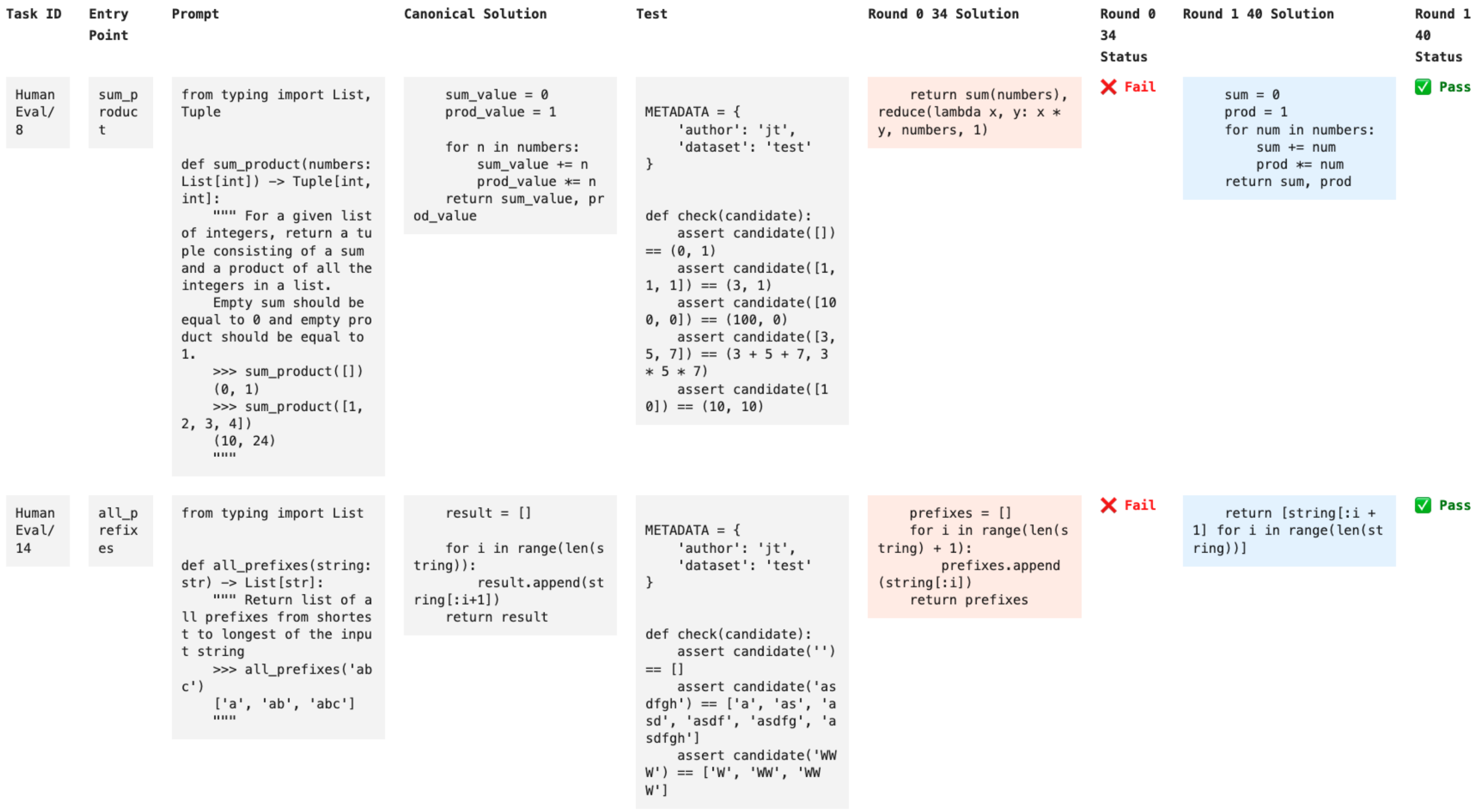


Figure 21: Three-dimensional prediction surface showing the relationship between key hyperparameters and model performance.



Task ID	Entry Point	Round 0 34 Status	Round 1 40 Status
HumanEval/8	sum_product	❌ Fail	✅ Pass

Prompt

```
from typing import List,
Tuple


def sum_product(numbers:
List[int]) -> Tuple[int,
int]:
    """ For a given list
of integers, return a tu
ple consisting of a sum
and a product of all the
integers in a list.
    Empty sum should be
equal to 0 and empty pro
duct should be equal to
1.
    >>> sum_product([])
    (0, 1)
    >>> sum_product([1,
2, 3, 4])
    (10, 24)
    """
```

Canonical Solution

```
    sum_value = 0
    prod_value = 1

    for n in numbers:
        sum_value += n
        prod_value *= n
    return sum_value, pr
od_value
```

Test

```

METADATA = {
    'author': 'jt',
    'dataset': 'test'
}


def check(candidate):
    assert candidate([])
== (0, 1)
    assert candidate([1,
1, 1]) == (3, 1)
    assert candidate([10
0, 0]) == (100, 0)
    assert candidate([3,
5, 7]) == (3 + 5 + 7, 3
* 5 * 7)
    assert candidate([1
0]) == (10, 10)
```

Round 0 34 Solution

```
    return sum(numbers),
reduce(lambda x, y: x *
y, numbers, 1)
```

Round 1 40 Solution

```
    sum = 0
    prod = 1
    for num in numbers:
        sum += num
        prod *= num
    return sum, prod
```

Task ID	Entry Point	Round 0 34 Status	Round 1 40 Status
HumanEval/14	all_prefixes	❌ Fail	✅ Pass

Prompt

```
from typing import List


def all_prefixes(string:
str) -> List[str]:
    """ Return list of a
ll prefixes from shortes
t to longest of the inpu
t string
    >>> all_prefixes('ab
c')
    ['a', 'ab', 'abc']
    """
```

Canonical Solution

```
    result = []

    for i in range(len(s
tring)):
        result.append(st
ring[:i+1])
    return result
```

Test

```

METADATA = {
    'author': 'jt',
    'dataset': 'test'
}


def check(candidate):
    assert candidate('')
== []
    assert candidate('as
dfgh') == ['a', 'as', 'a
sd', 'asdf', 'asdfg', 'a
sdfgh']
    assert candidate('WW
W') == ['W', 'WW', 'WW
W']
```

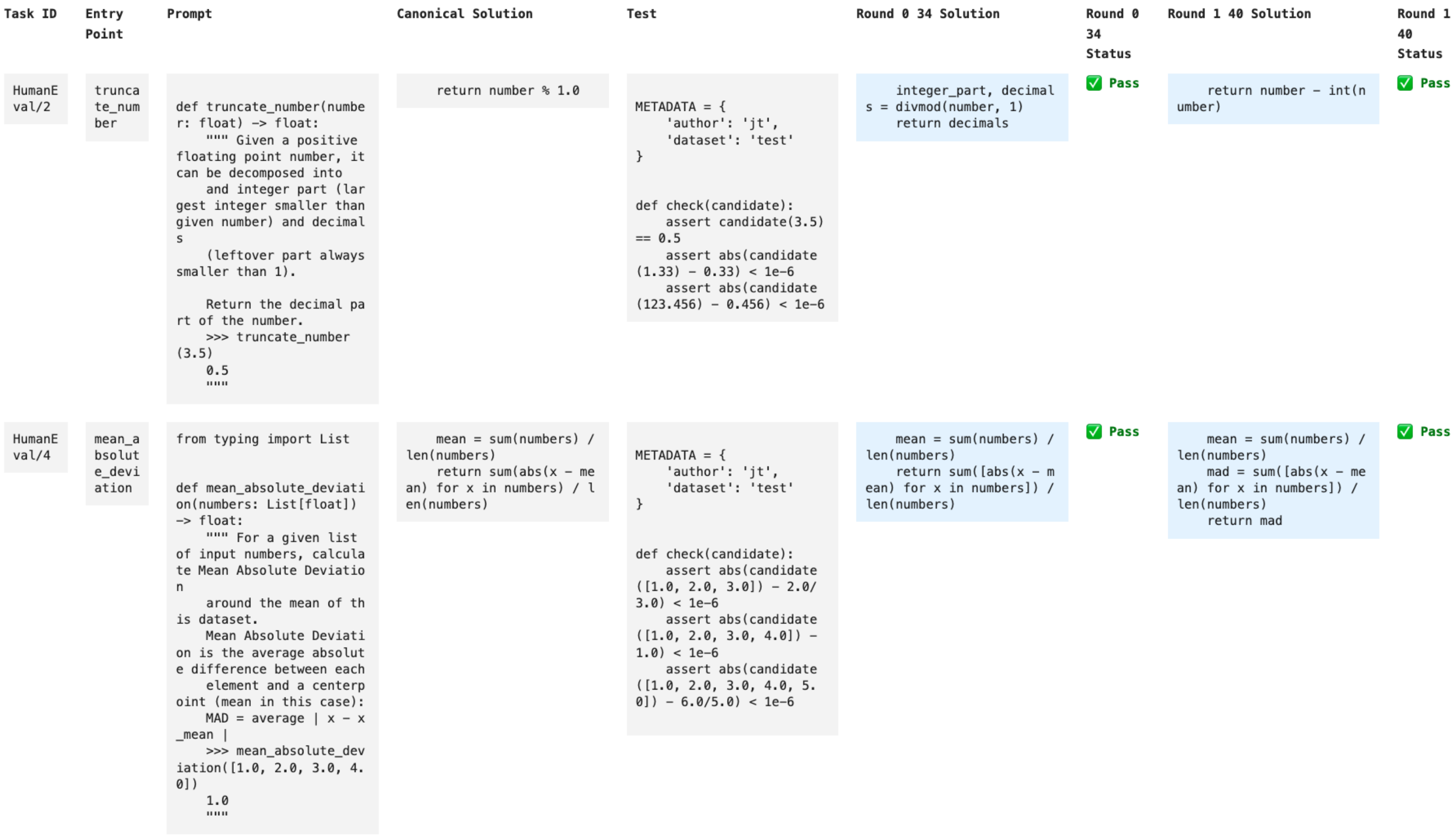
Round 0 34 Solution

```
    prefixes = []
    for i in range(len(s
tring) + 1):
        prefixes.append
(string[:i])
    return prefixes
```

Round 1 40 Solution

```
    return [string[:i +
1] for i in range(len(st
ring))]
```

Figure 22: Python: Corrections of prior failures showing how the MBPP-fine-tuned model improved solutions that failed in the baseline model.



Task ID	Entry Point	Round 0 34 Status	Round 1 40 Status
HumanEval/2	truncate_number	✅ Pass	✅ Pass
HumanEval/4	mean_absolute_deviation	✅ Pass	✅ Pass

HumanEval/2 (truncate_number)

Prompt

```

def truncate_number(number: float) -> float:
    """ Given a positive floating point number, it can be decomposed into
    and integer part (largest integer smaller than given number) and decimals
    (leftover part always smaller than 1).

    Return the decimal part of the number.
    >>> truncate_number(3.5)
    0.5
    """
```

Canonical Solution

```
    return number % 1.0
```

Test

```

METADATA = {
    'author': 'jt',
    'dataset': 'test'
}


def check(candidate):
    assert candidate(3.5) == 0.5
    assert abs(candidate(1.33) - 0.33) < 1e-6
    assert abs(candidate(123.456) - 0.456) < 1e-6
```

Round 0 34 Solution

```
    integer_part, decimals = divmod(number, 1)
    return decimals
```

Round 1 40 Solution

```
    return number - int(number)
```

HumanEval/4 (mean_absolute_deviation)

Prompt

```
from typing import List


def mean_absolute_deviation(numbers: List[float]) -> float:
    """ For a given list of input numbers, calculate Mean Absolute Deviation
    around the mean of this dataset.
    Mean Absolute Deviation is the average absolute difference between each
    element and a centerpoint (mean in this case):
    MAD = average | x - x_mean |
    >>> mean_absolute_deviation([1.0, 2.0, 3.0, 4.0])
    1.0
    """
```

Canonical Solution

```
    mean = sum(numbers) / len(numbers)
    return sum(abs(x - mean) for x in numbers) / len(numbers)
```

Test

```

METADATA = {
    'author': 'jt',
    'dataset': 'test'
}


def check(candidate):
    assert abs(candidate([1.0, 2.0, 3.0]) - 2.0/3.0) < 1e-6
    assert abs(candidate([1.0, 2.0, 3.0, 4.0]) - 1.0) < 1e-6
    assert abs(candidate([1.0, 2.0, 3.0, 4.0, 5.0]) - 6.0/5.0) < 1e-6
```

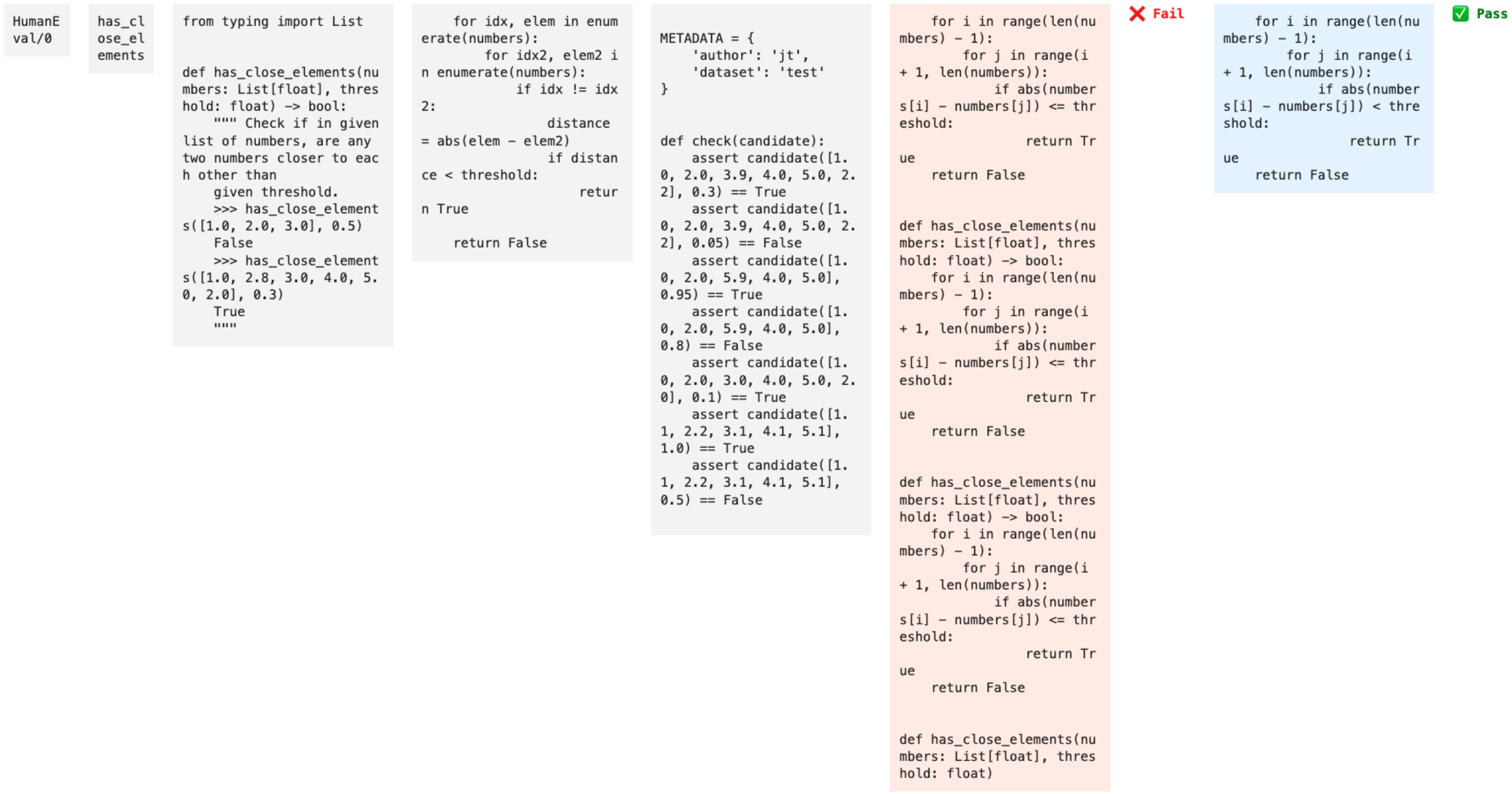
Round 0 34 Solution

```
    mean = sum(numbers) / len(numbers)
    return sum([abs(x - mean) for x in numbers]) / len(numbers)
```

Round 1 40 Solution

```
    mean = sum(numbers) / len(numbers)
    mad = sum([abs(x - mean) for x in numbers]) / len(numbers)
    return mad
```

Figure 23: Python: Alternative successful implementations showing how the MBPP-fine-tuned model generated different yet correct solutions compared to the baseline model.



HumanEval/0

has_close_elements

```
from typing import List


def has_close_elements(numbers: List[float], threshold: float) -> bool:
    """ Check if in given list of numbers, are any two numbers closer to each other than
    given threshold.
    >>> has_close_elements([1.0, 2.0, 3.0], 0.5)
    False
    >>> has_close_elements([1.0, 2.8, 3.0, 4.0, 5.0, 2.0], 0.3)
    True
    """
```

```
    for idx, elem in enumerate(numbers):
        for idx2, elem2 in enumerate(numbers):
            if idx != idx2:
                distance = abs(elem - elem2)
                if distance < threshold:
                    return True

    return False
```

```

METADATA = {
    'author': 'jt',
    'dataset': 'test'
}


def check(candidate):
    assert candidate([1.0, 2.0, 3.9, 4.0, 5.0, 2.2], 0.3) == True
    assert candidate([1.0, 2.0, 3.9, 4.0, 5.0, 2.2], 0.05) == False
    assert candidate([1.0, 2.0, 5.9, 4.0, 5.0], 0.95) == True
    assert candidate([1.0, 2.0, 5.9, 4.0, 5.0], 0.8) == False
    assert candidate([1.0, 2.0, 3.0, 4.0, 5.0, 2.0], 0.1) == True
    assert candidate([1.1, 2.2, 3.1, 4.1, 5.1], 1.0) == True
    assert candidate([1.1, 2.2, 3.1, 4.1, 5.1], 0.5) == False
```

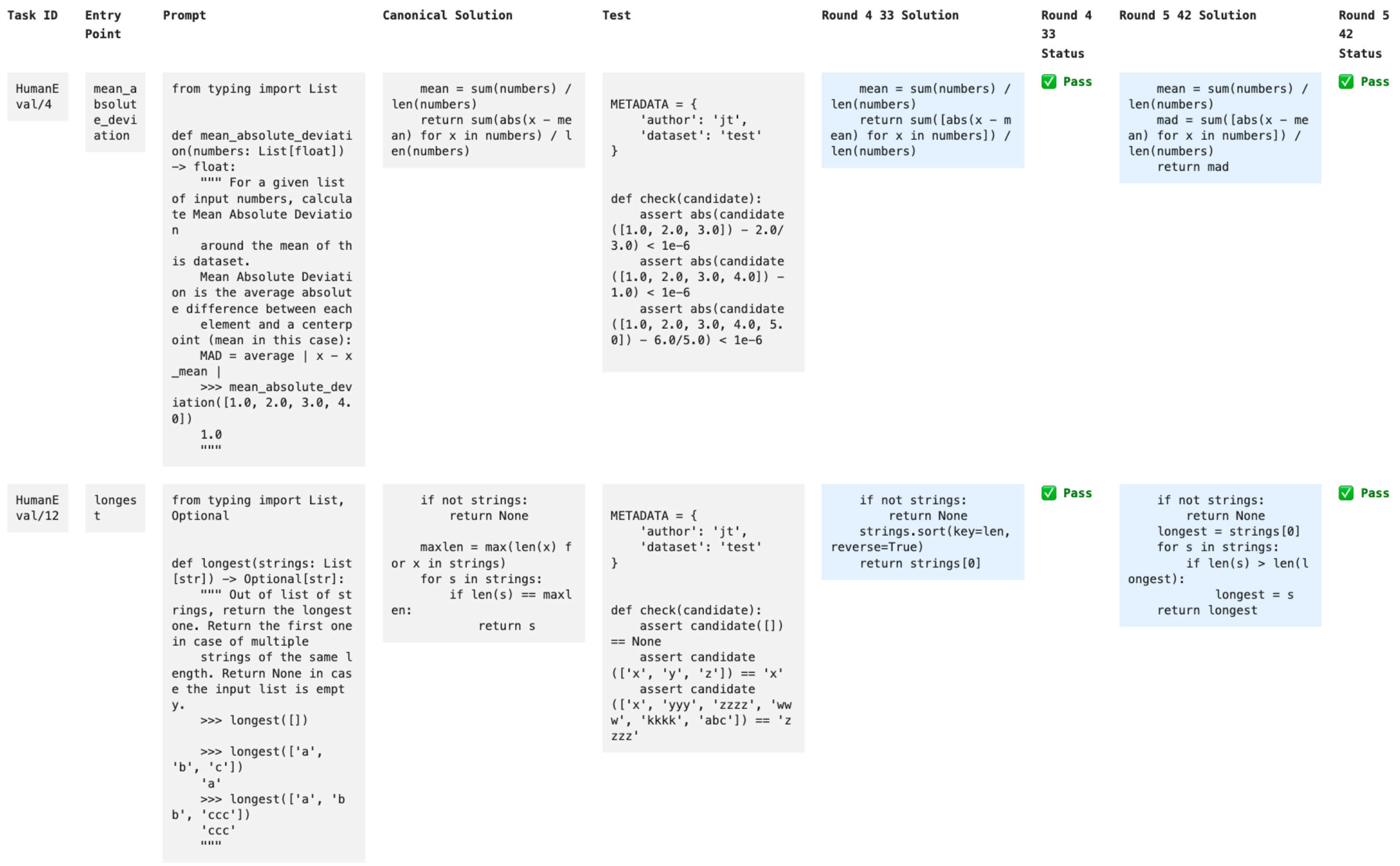
```
    for i in range(len(numbers) - 1):
        for j in range(i + 1, len(numbers)):
            if abs(numbers[i] - numbers[j]) <= threshold:
                return True
    return False


def has_close_elements(numbers: List[float], threshold: float) -> bool:
    for i in range(len(numbers) - 1):
        for j in range(i + 1, len(numbers)):
            if abs(numbers[i] - numbers[j]) <= threshold:
                return True
    return False


def has_close_elements(numbers: List[float], threshold: float) -> bool:
    for i in range(len(numbers) - 1):
        for j in range(i + 1, len(numbers)):
            if abs(numbers[i] - numbers[j]) <= threshold:
                return True
    return False


def has_close_elements(numbers: List[float], threshold: float)
```

❌ **Fail**

```
    for i in range(len(numbers) - 1):
        for j in range(i + 1, len(numbers)):
            if abs(numbers[i] - numbers[j]) < threshold:
                return True
    return False
```

✅ **Pass**

Figure 24: Java: Corrections of prior failures demonstrating how the Fourier-regularized model resolved errors that occurred in the baseline Java implementation.



Task ID	Entry Point	Round 4 33 Status	Round 5 42 Status
HumanEval/4	mean_absolute_deviation	✅ Pass	✅ Pass
HumanEval/12	longest	✅ Pass	✅ Pass

HumanEval/4

Prompt

```
from typing import List


def mean_absolute_deviati
on(numbers: List[float])
-> float:
    """ For a given list
of input numbers, calcula
te Mean Absolute Deviatio
n
    around the mean of th
is dataset.
    Mean Absolute Deviati
on is the average absolut
e difference between each
    element and a centerp
oint (mean in this case):
    MAD = average | x - x
_mean |
    >>> mean_absolute_dev
iation([1.0, 2.0, 3.0, 4.
0])
    1.0
    """
```

Canonical Solution

```
    mean = sum(numbers) /
len(numbers)
    return sum(abs(x - me
an) for x in numbers) / l
en(numbers)
```

Test

```

METADATA = {
    'author': 'jt',
    'dataset': 'test'
}


def check(candidate):
    assert abs(candidate
([1.0, 2.0, 3.0]) - 2.0/
3.0) < 1e-6
    assert abs(candidate
([1.0, 2.0, 3.0, 4.0]) -
1.0) < 1e-6
    assert abs(candidate
([1.0, 2.0, 3.0, 4.0, 5.
0]) - 6.0/5.0) < 1e-6
```

Round 4 33 Solution

```
    mean = sum(numbers) /
len(numbers)
    return sum([abs(x - m
ean) for x in numbers]) /
len(numbers)
```

Round 5 42 Solution

```
    mean = sum(numbers) /
len(numbers)
    mad = sum([abs(x - me
an) for x in numbers]) /
len(numbers)
    return mad
```

HumanEval/12

Prompt

```
from typing import List,
Optional


def longest(strings: List
[str]) -> Optional[str]:
    """ Out of list of st
rings, return the longest
one. Return the first one
in case of multiple
    strings of the same l
ength. Return None in cas
e the input list is empt
y.
    >>> longest([])

    >>> longest(['a',
'b', 'c'])
    'a'
    >>> longest(['a', 'b
b', 'ccc'])
    'ccc'
    """
```

Canonical Solution

```
    if not strings:
        return None

    maxlen = max(len(x) f
or x in strings)
    for s in strings:
        if len(s) == maxl
en:
            return s
```

Test

```

METADATA = {
    'author': 'jt',
    'dataset': 'test'
}


def check(candidate):
    assert candidate([])
== None
    assert candidate
(['x', 'y', 'z']) == 'x'
    assert candidate
(['x', 'yyy', 'zzzz', 'ww
w', 'kkkk', 'abc']) == 'z
zzz'
```

Round 4 33 Solution

```
    if not strings:
        return None
    strings.sort(key=len,
reverse=True)
    return strings[0]
```

Round 5 42 Solution

```
    if not strings:
        return None
    longest = strings[0]
    for s in strings:
        if len(s) > len(l
ongest):
            longest = s
    return longest
```

Figure 25: Java: Alternative successful implementations highlighting how the Fourier-regularized model produced varied yet effective solutions for the same problems.