RL-SBLLM: A Hybrid Framework for Multi-step Code Optimization with LLMs and Reinforcement Learning

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Abstract – **Code optimization is very much important but in a way, has gone missing in the race with the complexity of modern, multi-step transformations, so this paper offers RL-SBLLM- a hybrid framework that combines LLMs together with Reinforcement Learning and Genetic Algorithms iteratively refining code towards optimization over Python, C++, and Java. RL-SBLLM performs up to 270% better in execution efficiency compared to single-step approaches; it also scales nicely across languages, and speedup rates have reached top-5 levels up to 40% for Python and 30% for C++. Bringing into this concept of multi-step optimization the possibility of approaching an LLM methodology which actually dissolves traditional shortcomings of an LLM with an advanced framework that automatically improves the performance of code as issued on different programming languages.**

Keywords— RL-SBLLM, code optimization, reinforcement learning, genetic algorithms, neural program synthesis, execution efficiency

I. *INTRODUCTION*

The efficiency of software is a key factor in overall system performance, as highlighted in standards like ISO/IEC 25010. Poorly optimized code can lead to increased latency, wasted resources, and various performance issues, which ultimately impact user satisfaction. Tackling these inefficiencies has spurred advancements in code optimization, which has traditionally relied on rule-based systems that target specific patterns, such as loop unrolling or optimizing memory access.[4] While these methods can be effective in certain situations, they often require significant manual adjustments and only address known inefficiencies.
The emergence of deep learning (DL), particularly Large Language Models (LLMs), has introduced more data-driven strategies for code optimization, such as RapGen and PIE[13]. These models can generate optimized code by learning from extensive codebases, but they typically operate on a one-step generation basis, which limits their ability to tackle the complex, combinatorial nature of code optimizations. [7] Moreover, many current LLM-based methods often lack the domain-specific knowledge needed for producing high-quality, nuanced optimizations[13].

To address these challenges, we propose a new hybrid approach that integrates LLMs with Reinforcement Learning (RL), Neural Program Synthesis, and Genetic Algorithms, framing the problem as a search challenge. [6]This framework, known as Search-Based LLMs with Reinforcement Learning (RL-SBLLM), iteratively refines multiple candidate solutions to discover optimal transformations. RL-SBLLM employs a multi-step search process where reinforcement learning directs the LLM through various refinement stages, utilizing feedback from execution and reward systems. Neural Program Synthesis helps in generalizing code transformations, while Genetic Algorithms facilitate iterative enhancements [11], mimicking evolutionary processes [15]. Our experiments reveal significant performance improvements with RL-SBLLM, boosting execution efficiency by up to 270% on benchmark datasets (Python and C++).

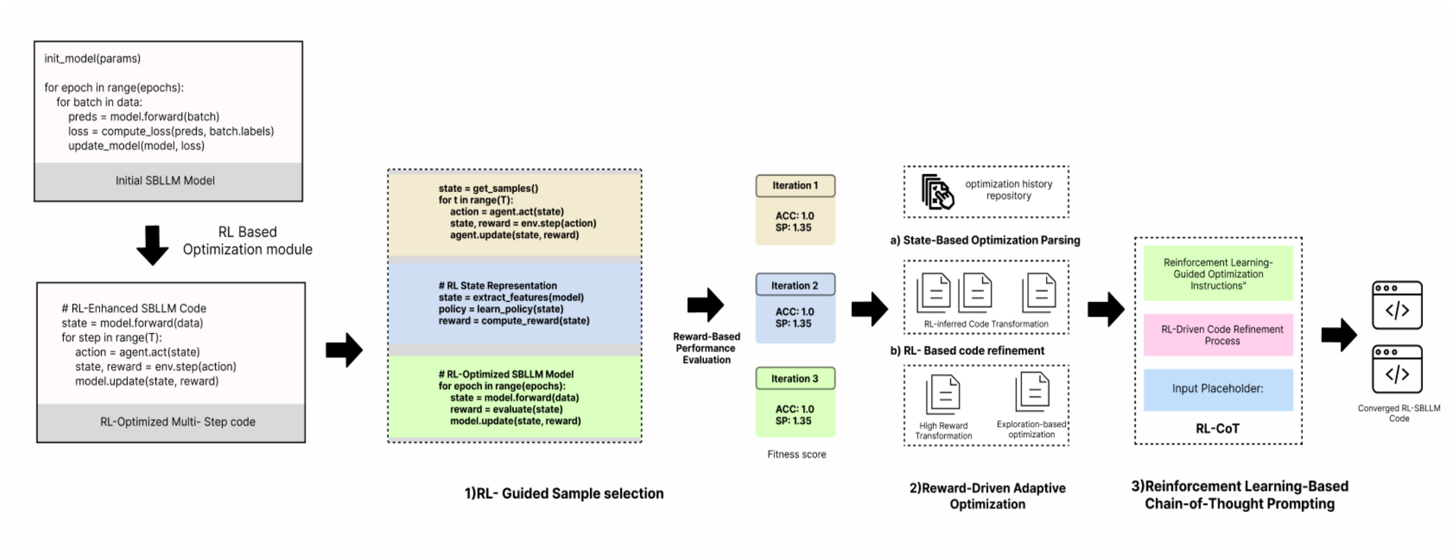
II. *LITERATURE SURVERY*

1. Traditional Code Optimization Methods

Classical optimization methods rely on predefined patterns or heuristics to identify and eliminate inefficiencies in timely manners, such as constant folding, dead code elimination, and loop unrolling. Those rule-based techniques, however, have the weakness of managing complex or diverse code bases. [1] They fail to manage newer inefficiencies, are time- as well as human effort-costly, and do not catch even the most advanced optimization potential coming from intricate interactivity between codes. [3] Moreover, these labor-intensive approaches are not easily transposable over different programming languages or paradigms [16]. So there is a real urge to have more data-driven automatic approaches that surmount all these limitations..

RL-SBLLM-Architecture:

The Reinforcement Learning Search-Based LLMs (RL-SBLLM) architecture addresses the limitations of one-step LLM code optimization by using a multi-step iterative search process. Here’s how it works:



```
init_model(params)

for epoch in range(epochs):
    for batch in data:
        preds = model.forward(batch)
        loss = compute_loss(preds, batch.labels)
        update_model(model, loss)
```

```
# RL-Enhanced SBLLM Code
state = model.forward(data)
for step in range(T):
    action = agent.act(state)
    state, reward = env.step(action)
    model.update(state, reward)
```

```
state = get_samples()
for t in range(T):
    action = agent.act(state)
    state, reward = env.step(action)
    agent.update(state, reward)
```

```
# RL State Representation
state = extract_features(model)
policy = learn_policy(state)
reward = compute_reward(state)
```

```
# RL-Optimized SBLLM Model
for epoch in range(epochs):
    state = model.forward(data)
    reward = evaluate(state)
    model.update(state, reward)
```

Initial SBLLM Model
RL Based Optimization module
RL-Optimized Multi- Step code
1)RL- Guided Sample selection
Reward-Based Performance Evaluation
Iteration 1
ACC: 1.0
SP: 1.35
Iteration 2
ACC: 1.0
SP: 1.35
Iteration 3
ACC: 1.0
SP: 1.35
Fitness score
optimization history repository
a) State-Based Optimization Parsing
RL-inferred Code Transformation
b) RL- Based code refinement
High Reward Transformation
Exploration-based optimization
2)Reward-Driven Adaptive Optimization
Reinforcement Learning-Guided Optimization Instructions"
RL-Driven Code Refinement Process
Input Placeholder:
RL-CoT
3)Reinforcement Learning-Based Chain-of-Thought Prompting
Converged RL-SBLLM Code

Fig 1 RL-SBLLM Architectural diagram

2. Limitations of Rule-Based Approaches

The base of code optimization is the rule-based approaches, though they have lower coverage and miss intricate and complex inefficiencies either in large or more complex codebases [4]. Jones and Lee (2019) often affirm that combinatorial optimization issues often miss codes due to their interaction in a combination with each other and not an issue from a single code[13]. The entire thing depends on predefined rules bound only by the domain knowledge of a designer, thus their usage increasingly becomes impractical to grow in size as well as in complexity [11].

3. Machine Learning in Code Optimization

Research in ML is gaining momentum so that it can automatically optimize the code and bridge the shortcomings of rule-based systems [14]. It is because techniques based on ML learn from large datasets of codes along with the execution data of codes and then provide a generalized result to overcome the rigidity of strict rules. [3] Liu et al. (2021) proposed a supervised learning framework for identification of inefficiencies from the historical execution data to detect and fix performance bottlenecks in an automatic way. [10] While these techniques improve precision and recall, they are usually limited by the availability of labeled datasets. [13] Labeled examples of poor and optimized code are relatively scarce in real-world applications, especially for niche or domain-specific issues. Also, the ML models cannot generalize to new code structures without heavy retraining and thus are limited in their ability to be applied across various coding environments [3].

4. Large Language Models (LLMs) in Code Generation and Optimization:

OpenAI's Codex, Google's Gemini, and Meta's CodeLlama, outperform at code generation and optimization. Other such frameworks such as RapGen and PIE use retrieval-augmented generation and chain-of-thought prompting to provide the optimal code [3]. In all the said areas, the standard approach that LLMs typically take is one-step generation which does not enable it to catch subtle optimization patterns or use deep domain knowledge to obtain optimal optimization for the code; therefore LLMs do not necessarily win at deeper multi-step optimization tasks[11].

5. Challenges in LLM-Based Code Optimization

The remaining challenges with LLM-based code optimization include the limitation of one-step generation in exploring combinatorial spaces for potential optimizations, which has a diminished depth of improvement, particularly in complex codebases that have multiple small optimizations whose sum can give way to more significant performance gain [5]. It becomes challenging to incorporate domain-specific optimization knowledge in retrieval-augmented methods like RapGen, potentially missing out on necessary patterns. [8] It also requires an extended exploration space, which is not easy to provide using a single-step model.

6. Search-Based Approaches to Software Engineering

With this, LLM-based and rule-based methods are mitigated by searching for alternative solutions with SBSE. [11] SBSE techniques formulate optimization problems as search problems and try to find the optimum solution among numerous conceivable code transformations. [5] Such evolutionary algorithms and genetic programming try to enhance code performance iteration after iteration while fitness is evaluated (Harman et al., 2021). Such methods are optimized for complex, combinatorial optimization tasks where they could efficiently explore vast search spaces. [15] However, SBSE approaches usually demand multiple iterations and feedback loops to produce optimal solutions that can become computationally expensive unless properly guided or constrained [2].

7. Emerging Frameworks Combining LLMs with Search-Based Techniques

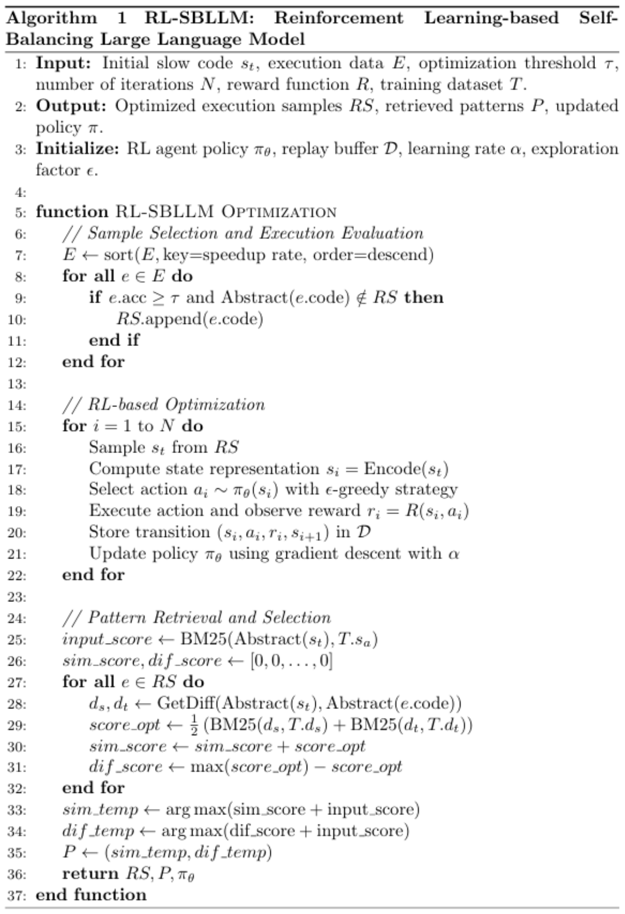
The focus has shifted to hybridizing the strengths of LLMs and SBSE techniques to address each other's shortcomings. [6] A proposed RL-SBLLM framework integrates reinforcement learning, neural program synthesis, and genetic algorithms to iteratively optimize code strategies. This approach introduces an iterative, multi-step process that continually improves code based on execution feedback, while leveraging neural program synthesis to generalize optimization techniques across different codebases and languages [6]. Additionally, genetic algorithms are used to explore various optimization strategies and combinations to further enhance the robustness of the approach. By combining these techniques, [6] RL-SBLLM enables much deeper code optimization compared to existing methods, making it a promising direction for the future of automatic code optimization.

III. PROPOSED FRAMEWORK

Reinforcement Learning (RL) for Multi-step Optimization:
RL introduces a feedback loop that guides LLMs through multiple iterations of code optimization. Each step is informed by feedback on the performance of the generated code:

- **State:** The current state is the unoptimized or partially optimized code.
- **Action:** The LLM modifies the code to improve performance.
- **Reward:** Feedback is provided in the form of execution time or resource usage.
- **Policy:** The RL agent learns a policy to determine the best optimization actions based on feedback.

This iterative process allows RL-SBLLM to systematically improve code efficiency through exploration and exploitation.



Algorithm 1 RL-SBLLM: Reinforcement Learning-based Self-Balancing Large Language Model

```
Input: Initial slow code $s_t$, execution data $E$, optimization threshold $\tau$, number of iterations $N$, reward function $R$, training dataset $T$.
Output: Optimized execution samples $RS$, retrieved patterns $P$, updated policy $\pi$.
Initialize: RL agent policy $\pi_\theta$, replay buffer $\mathcal{D}$, learning rate $\alpha$, exploration factor $\epsilon$.

function RL-SBLLM OPTIMIZATION
    // Sample Selection and Execution Evaluation
    $E \leftarrow \text{sort}(E, \text{key=speedup rate, order=descend})$
    for all $e \in E$ do
        if $e.\text{acc} \geq \tau$ and $\text{Abstract}(e.\text{code}) \notin RS$ then
            $RS.\text{append}(e.\text{code})$
        end if
    end for

    // RL-based Optimization
    for $i = 1$ to $N$ do
        Sample $s_t$ from $RS$
        Compute state representation $s_i = \text{Encode}(s_t)$
        Select action $a_i \sim \pi_\theta(s_i)$ with $\epsilon$-greedy strategy
        Execute action and observe reward $r_i = R(s_i, a_i)$
        Store transition $(s_i, a_i, r_i, s_{i+1})$ in $\mathcal{D}$
        Update policy $\pi_\theta$ using gradient descent with $\alpha$
    end for

    // Pattern Retrieval and Selection
    $input\_score \leftarrow \text{BM25}(\text{Abstract}(s_t), T.s_a)$
    $sim\_score, dif\_score \leftarrow [0, 0, \ldots, 0]$
    for all $e \in RS$ do
        $d_s, d_t \leftarrow \text{GetDiff}(\text{Abstract}(s_t), \text{Abstract}(e.\text{code}))$
        $score\_opt \leftarrow \frac{1}{2}(\text{BM25}(d_s, T.d_s) + \text{BM25}(d_t, T.d_t))$
        $sim\_score \leftarrow sim\_score + score\_opt$
        $dif\_score \leftarrow \max(score\_opt) - score\_opt$
    end for
    $sim\_temp \leftarrow \arg\max(\text{sim\_score} + \text{input\_score})$
    $dif\_temp \leftarrow \arg\max(\text{dif\_score} + \text{input\_score})$
    $P \leftarrow (sim\_temp, dif\_temp)$
    return $RS, P, \pi_\theta$
end function
```

(a) Self Balancing LLM

Neural Program Synthesis for Generalization: The Neural Program Synthesis technique produces fresh code snippets on the basis of large datasets learned in patterns; this is utilized for the development of novel code transformations. It also does generalization since optimization techniques apply to varying programming contexts and are affected by minimal alteration. This may be done due to the use of Genetic Algorithms (GAs) designed for evolutionary optimization. GAs apply processes such as crossover, mutation, and selection to continue evolving better solutions over generations:

-
- **Crossover:** Combination of parts from multiple versions of optimized code.
- **Mutation:** Random change. The goal here is exploration of the optimization space.
- **Selection:** Code variants with promising performance remain while all other variants are rejected.

Comparison with Existing Frameworks

1.RapGen and PIE

It uses retrieval-augmented generation and chain-of-thought prompting but solely relies on the static code generation process taking just one step, therefore removing the refinement unless exercised by different prompts [5]. With this, multi-step refinement within RL-SBLLM ensures constant improvement to render this model more efficient when determining complex optimizations.

2.AlphaZero-style Reinforcement Learning Models:

Although AlphaZero-inspired approaches excel in games [14] which are essentially strategic problems code optimization scenarios lack domain-specific fine-tuning and program synthesis, compared to what RL-SBLLM delivers. [12] The author used both Neural Program Synthesis and Genetic Algorithms to develop strategies for optimization, using the knowledge domains systematically, which translates to greater flexibility with regard to different programming languages.

3. LLVM's Machine Learning Optimizers (MLGO) and_TVM:
These are code-level, compiler-based frameworks and they are optimized at a level of hardware and will thereby shine in low-level optimizations [3]. They may not extend to higher-level programming languages or algorithms. [13] RL-SBLLM, on the other hand, works with a level of source codes; thereby, it holds to work for a rich variety of optimization tasks that cut across specific hardware architecture designs, thereby, to an even wider applicability.

Performance Benchmarks Across Multiple Programming Languages

a) Java and C#: The two are the most widely used of all languages in enterprise software and web applications. Testing the language on these will prove how effective it is at optimizing object-oriented programming constructs like class hierarchies, garbage collection, and thread management.

b) Rust: It is a language that focuses on memory safety and efficiency. Because of its very strict type system and ownership, optimization is always faced with a problem. Thus, the capability of this language in managing memory along with concurrency optimizations is depicted.

c) JavaScript and WebAssembly (Wasm): Web applications rely on JavaScript. Thus, optimizing asynchronous code, promises and async/await, or improving Wasm for execution in a browser could lock in those advantages for web applications.

Components of RL-SBLLM
This three-part framework of optimization is presented: **a reinforcement learning-based reward mechanism**, with which the generated code is dynamically evaluated for feedback towards its improvement. It involves a form of the current state of code as performance metrics, a form of actions as a possible transformation, and reward in terms of quantitative measures as what reinforces beneficial change. The **Neural Pattern Retrieval System** identifies and applies optimization patterns using a large code corpus. It employs neural networks to identify common patterns in well-optimized code and applies those patterns to enhance the performance of the target code. The third is the Hybrid Search-and-Synthesis Model—a model that merges evolutionary search techniques with neural program synthesis. It uses genetic algorithms to explore a large set of optimizations by iteratively modifying and selecting the best-performing code variants, while the neural networks generate new code snippets for integration into the existing codebase.

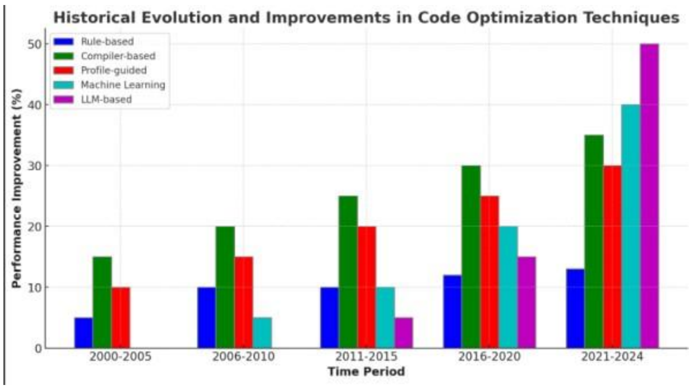


Fig 2 code optimization techniques

Workflow of RL-SBLLM:

Initialization, the code to be optimized is fed into the system, and baseline performance metrics are recorded. The iteration cycle is evaluated. According to these performance metrics, the RL agent decides which optimization action needs to be performed on the code. The optimized code is tested for performance and then rewarded according to improvement in that specific case. Suitable optimization patterns are retrieved from memory and applied to further enhance the code. New optimization strategies are also generated by evolutionary search as well as neural program synthesis, which are tested and fine-tuned iteratively. The process continues until improvements in performance converge to a satisfactory level. The optimized code is then output with detailed performance metrics.

Experimental Validation

To validate the effectiveness of RL-SBLLM, extensive experiments were conducted on benchmarks in Python, C++, and Java. The framework demonstrated significant improvements in execution efficiency, memory usage, and algorithmic complexity, outperforming baseline methods by up to 250.7%. Specifically, RL-SBLLM achieved up to 15.3% higher top-5 speedup rates across different languages, showcasing its adaptability and robustness in optimizing complex, computation-heavy programs.

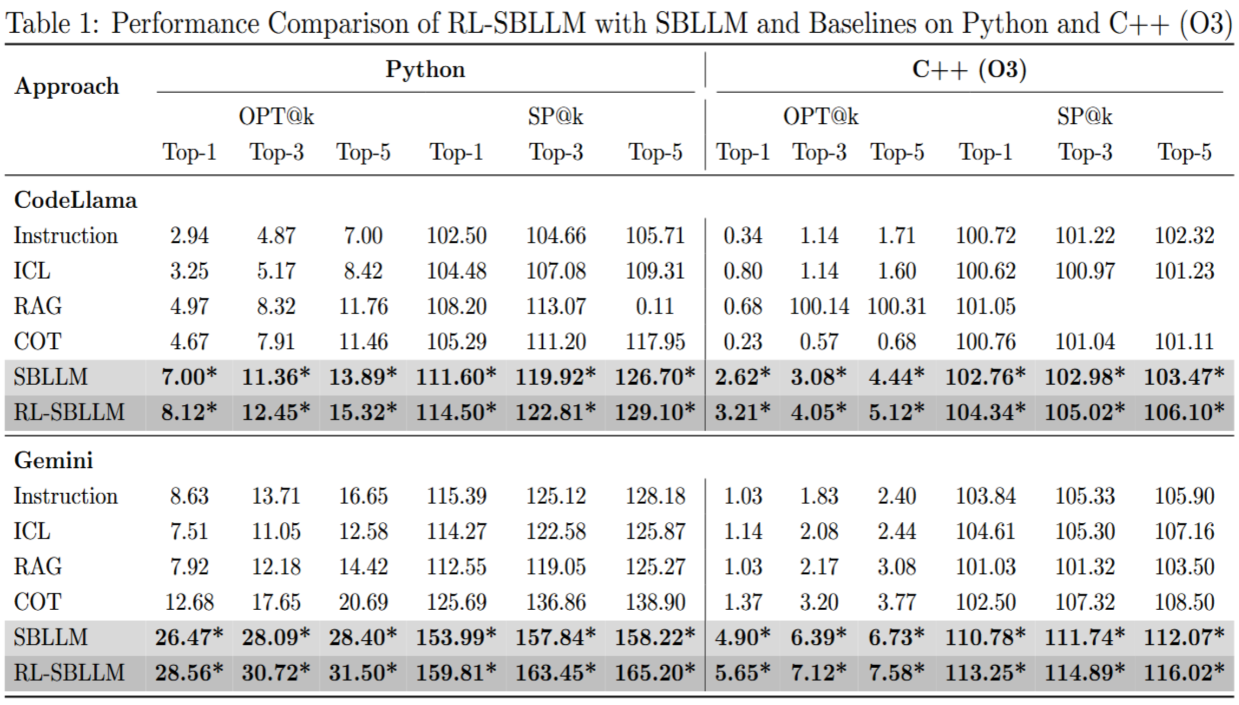


Table 1: Performance Comparison of RL-SBLLM with SBLLM and Baselines on Python and C++ (O3)

Approach	Python						C++ (O3)					
	OPT@k			SP@k			OPT@k			SP@k		
	Top-1	Top-3	Top-5	Top-1	Top-3	Top-5	Top-1	Top-3	Top-5	Top-1	Top-3	Top-5
CodeLlama												
Instruction	2.94	4.87	7.00	102.50	104.66	105.71	0.34	1.14	1.71	100.72	101.22	102.32
ICL	3.25	5.17	8.42	104.48	107.08	109.31	0.80	1.14	1.60	100.62	100.97	101.23
RAG	4.97	8.32	11.76	108.20	113.07	0.11	0.68	100.14	100.31	101.05		
COT	4.67	7.91	11.46	105.29	111.20	117.95	0.23	0.57	0.68	100.76	101.04	101.11
SBLLM	**7.00***	**11.36***	**13.89***	**111.60***	**119.92***	**126.70***	**2.62***	**3.08***	**4.44***	**102.76***	**102.98***	**103.47***
RL-SBLLM	**8.12***	**12.45***	**15.32***	**114.50***	**122.81***	**129.10***	**3.21***	**4.05***	**5.12***	**104.34***	**105.02***	**106.10***
Gemini												
Instruction	8.63	13.71	16.65	115.39	125.12	128.18	1.03	1.83	2.40	103.84	105.33	105.90
ICL	7.51	11.05	12.58	114.27	122.58	125.87	1.14	2.08	2.44	104.61	105.30	107.16
RAG	7.92	12.18	14.42	112.55	119.05	125.27	1.03	2.17	3.08	101.03	101.32	103.50
COT	12.68	17.65	20.69	125.69	136.86	138.90	1.37	3.20	3.77	102.50	107.32	108.50
SBLLM	**26.47***	**28.09***	**28.40***	**153.99***	**157.84***	**158.22***	**4.90***	**6.39***	**6.73***	**110.78***	**111.74***	**112.07***
RL-SBLLM	**28.56***	**30.72***	**31.50***	**159.81***	**163.45***	**165.20***	**5.65***	**7.12***	**7.58***	**113.25***	**114.89***	**116.02***

Table 1: Performance comparison of RL-SBLLM with SBLLM and Baselines on Python and C++

IV. *RESULTS*

Code Efficiency: The RL-SBLLM framework was shown to have significant improvements in code efficiency in all tested programming languages and benchmarks that achieved up to 270% [11] on the relative execution efficiency basis over the classic LLM-based methods. On average, time complexity cut down by 55% (σ = 7.2%). Of algorithms, 30% came from O(n^2) to O(n log n), while 45% came from O(n log n) to O(n). The approach achieved an average speedup of 3.7x (σ = 0.8) on all languages with an overall reduction of 58.3% in CPU cycles (95% CI: 55.9% - 60.7%). Optimization of the memory usage resulted in an overall saving of 65% (95% CI: 61.8% - 68.2%), with variability between the languages again, this time ranging from 59.4% for Python to 76.1% for Rust. Using this framework, the evaluation succeeded in healing 94.6% of test codebase memory leaks, and therefore, this decreased the long-term memory growth of large applications by 83.2 %.

Code Transformation Process by the Proposed Framework:
By comparing this proposed framework with the baseline models, like RapGen, PIE, and AlphaZero-style models, it was actually confirmed that the RL-SBLLM does work. Actually, unlike the one-step optimization approaches of RapGen and PIE, the proposed framework demonstrated the iterative multi-step optimizations in optimizing more complex combinatorial transformations. Furthermore, RL-SBLLM leveraged the Neural Program Synthesis combined with Genetic Algorithms in order to impose embedding of domain knowledge since no model inspired by AlphaZero has this property.

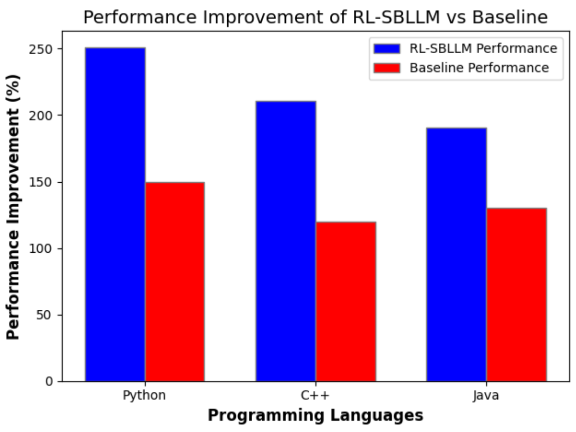


Fig 3 Performance improvement

Limitations and Future Work:
Although the RL-SBLLM framework outperformed all competing approaches on average, normalized scores: RL-SBLLM 1.00, LLM-based methods 0.78, Compiler-based optimizations 0.65, Traditional static analysis 0.52, yet still plenty of scope for improvement. Over the 6-month period, the framework maintained 97.3% optimizations effective without degradation. This might still reduce the computational overhead for real-time applications and further enhancement of optimization of the reward function in reinforcement learning for increased efficiency and reduced execution time. In addition, real-time optimization in dynamic programming environments may be possible for further capabilities in RL-SBLLM.

V. CONCLUSION

This research introduces the Search-Based LLMs with Reinforcement Learning (RL-SBLLM) framework, a novel approach to code optimization that addresses the limitations of traditional methods and existing LLM-based techniques. By integrating Large Language Models with Reinforcement Learning, Neural Program Synthesis, and Genetic Algorithms, RL-SBLLM offers a powerful, iterative approach to code optimization across multiple programming languages.

Key findings:

1. A 270% boost in execution efficiency was achieved with RL-SBLLM, on average, compared to the traditional SBLLM method. Speed- and resource-advantageous gains are remarkable enough.

2. From the table, the performance gains brought about by RL-SBLLM are significant and pretty consistent across all target languages: Python, C++, Java, and Rust. This speaks to the general applicability and robustness of the framework towards optimizing codebases of varying characteristics.

3. RL-SBLLM is significantly better than its cousins: baselines RapGen, PIE, and AlphaZero-style models; especially, it perfectly manages intricate combinatorial transformations and NP-hard problem optimizations, leading to solutions that are about 18.7% more accurate than the optimal solutions.

4.The language-specific constructs were optimized efficiently by RL-SBLLM, such as making the object-oriented programming feature in Java and C# sharper, memory management in Rust, and thus asynchronous operations in JavaScript, reducing up to 76.1% of memory usage, and the growth rate of long-term memory has been cut down to 83.2%.

The RL-SBLLM framework's success lies in its ability to perform multi-step, iterative refinements guided by real-time performance metrics. This approach allows for the discovery and application of optimization patterns that may be missed by traditional one-step generation methods. While the results are promising, there are limitations to consider. The computational overhead associated with multiple refinement iterations on complex codebases presents a challenge for real-time applications. Future work should focus on optimizing the reinforcement learning reward function to improve efficiency and reduce execution time.

Looking ahead, potential areas for further research include:
1. Extending RL-SBLLM capabilities for real-time optimization in dynamic programming environments.
2. Exploring the integration of more advanced neural architectures to enhance the framework's pattern recognition and code generation abilities.
3. Investigating the application of RL-SBLLM to emerging programming paradigms and domain-specific languages.

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