

# SLM-Bench: A Comprehensive Benchmark of Small Language Models on Environmental Impacts—Extended Version

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## Abstract

Small Language Models (SLMs) offer computational efficiency and accessibility, yet a systematic evaluation of their performance and environmental impact remains lacking. We introduce SLM-Bench, the first benchmark specifically designed to assess SLMs across multiple dimensions, including accuracy, computational efficiency, and sustainability metrics. SLM-Bench evaluates 15 SLMs on 9 NLP tasks using 23 datasets spanning 14 domains. The evaluation is conducted on 4 hardware configurations, providing a rigorous comparison of their effectiveness. Unlike prior benchmarks, SLM-Bench quantifies 11 metrics across correctness, computation, and consumption, enabling a holistic assessment of efficiency trade-offs. Our evaluation considers controlled hardware conditions, ensuring fair comparisons across models. We develop an open-source benchmarking pipeline with standardized evaluation protocols to facilitate reproducibility and further research. Our findings highlight the diverse trade-offs among SLMs, where some models excel in accuracy while others achieve superior energy efficiency. SLM-Bench sets a new standard for SLM evaluation, bridging the gap between resource efficiency and real-world applicability.

## 1 Introduction

Recent advancements in Language Models (LMs) have profoundly influenced a wide range of domains, including finance (Theuma and Shareghi, 2024), healthcare (Yang et al., 2024a), and manufacturing (Li et al., 2024). These models have demonstrated exceptional capabilities in retaining vast amounts of knowledge (Zheng et al., 2023), solving highly complex tasks (Bursztyn et al., 2022), and conducting intricate reasoning processes (Yang et al., 2024b) that closely align

with human-level intentions. Their ability to understand context, generate coherent text, and adapt to diverse applications has made them indispensable tools in both academic research and industry practices.

However, the impressive performance of LMs often comes at a significant cost. The large number of parameters that enable their functionality requires extensive computational resources (Lv et al., 2024), leading to prohibitively high operational expenses. Additionally, these models demand intensive energy consumption, which not only drives up costs but also contributes to substantial environmental challenges. The carbon footprint associated with training and deploying Large Language Models (LLMs) has raised concerns about their sustainability (Faiz et al., 2024), as they emit significant amounts of CO<sub>2</sub>. These issues underline the pressing need for more efficient and environmentally conscious alternatives to LLMs, particularly in an era of growing awareness around climate change and resource optimization.

SLMs (Gao et al., 2023; Magister et al., 2023) have emerged as a promising solution to mitigate the negative impacts associated with LLMs. By significantly reducing the number of parameters, SLMs aim to lower computational costs, minimize energy consumption, and decrease the associated carbon emissions, making them a more sustainable alternative. Their potential has garnered increasing attention from both academic researchers and industry practitioners, positioning SLMs as a practical choice for applications requiring efficiency and scalability.

Despite their growing prominence, a notable gap exists in the systematic evaluation of SLMs. Currently, there is no dedicated benchmark that

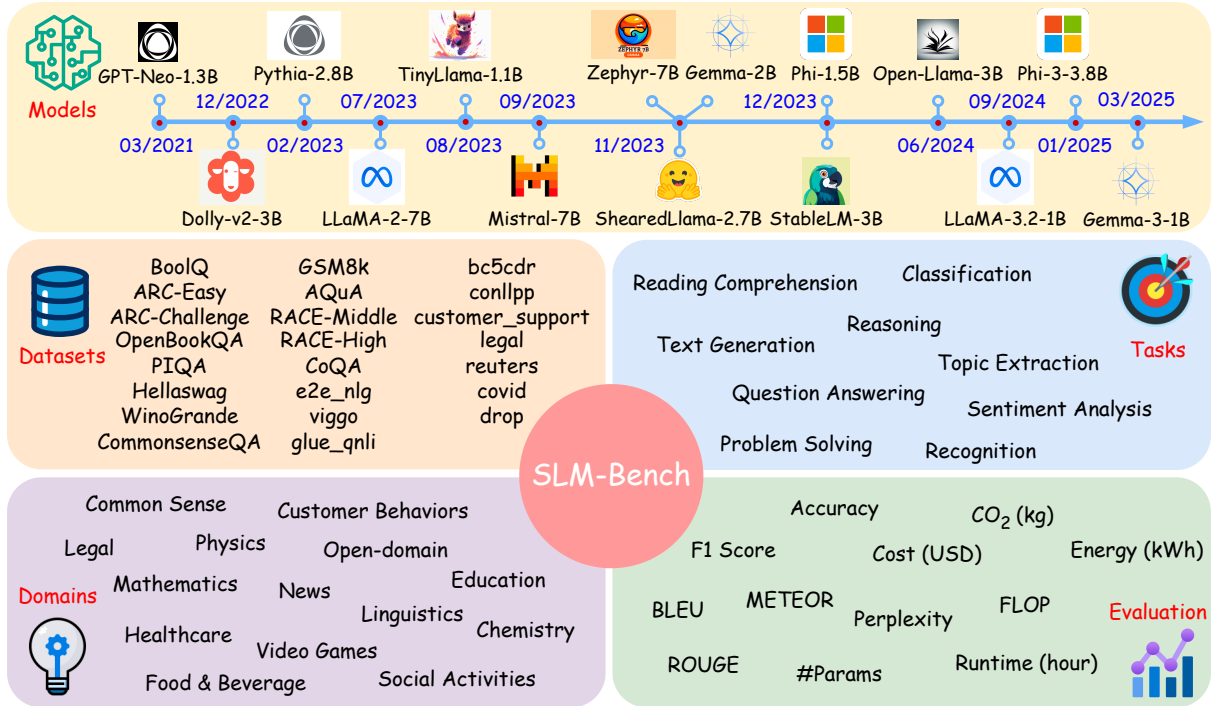


Figure 1: Overview of SLM-Bench

comprehensively assesses the performance of SLMs across diverse tasks while also quantifying their environmental impacts. This lack of standardized evaluation hinders a deeper understanding of their practical implications, particularly in resource-constrained environments where efficiency and sustainability are paramount. Addressing this gap is essential to unlock the full potential of SLMs and guide their development and deployment to balance performance with environmental responsibility.

In this paper, we aim to address the existing gap by introducing SLM-Bench (Small Language Model-Benchmark), a comprehensive benchmarking framework designed to evaluate SLMs across diverse settings with a focus on their environmental impacts. The insights gained from SLM-Bench will be instrumental in guiding the development and deployment of SLM-powered applications, particularly in resource-constrained environments. SLM-Bench is characterized by three primary features: (i) **Focus on SLMs**: Unlike existing benchmarks that predominantly emphasize LLMs (Myrzakhan et al., 2024), SLM-Bench evaluates SLMs that are computationally efficient and accessible to a wider range of users and sys-

tems. (ii) **Measurement of Environmental Impacts**: A unique aspect of SLM-Bench is its integration of metrics for energy consumption and CO<sub>2</sub> emissions. This allows for a holistic assessment of the sustainability of SLMs, addressing a crucial aspect often overlooked in benchmarking efforts. (iii) **Evaluation Across Diverse Settings**: SLM-Bench rigorously evaluates 15 SLMs on 9 tasks using 23 datasets from 14 domains. The evaluation is conducted on 4 hardware configurations, providing a comprehensive analysis of their performance across varied scenarios. This extensive evaluation ensures a deeper understanding of SLM capabilities and trade-offs.

SLM-Bench is illustrated in Figure 1, where we provide an overview of its key components, including the selected SLMs, the datasets used, the selected domains, the tasks evaluated, and the metrics employed for assessment. To the best of our knowledge, SLM-Bench represents the first systematic benchmarking framework dedicated to the evaluation of SLMs with a specific focus on their environmental impacts. We hope that SLM-Bench will drive construction through evaluation, facilitating the development of SLMs in many more applications. Aiming

at reproducibility and transparency, the source code and homepage for SLM-Bench are provided at <https://anonymous.4open.science/r/slm-bench-experiments-87F6> and <https://slm-bench.github.io/leaderboard>, respectively which will be continuously updated to catch up the state-of-the-arts. In summary, our contributions are as follows.

- We introduce SLM-Bench, a comprehensive benchmark of SLMs, which are computationally efficient and more accessible for deployment in resource-constrained environments.
- We consider the environmental impacts, such as energy consumption and CO<sub>2</sub> emissions, enabling a holistic assessment of the sustainability of SLMs.
- We extensively evaluate 15 SLMs across 9 tasks using 23 datasets from 14 domains on 4 hardware configurations, offering a thorough understanding of their capabilities and limitations in various contexts.

## 2 Related Work

### 2.1 Small Language Models

LLMs, such as GPT-4 (OpenAI, 2023), LLaMA (Touvron et al., 2023), and PaLM (Vilar et al., 2023), have demonstrated exceptional capabilities across various tasks. However, their large parameter sizes lead to high computational costs (Sharir et al., 2020), energy demands (Strubell et al., 2020), and environmental impacts (Dhar, 2020). To address these challenges, SLMs have gained attention for their efficiency and scalability. Techniques like model pruning (Zhang et al., 2024b; Sun et al., 2024; Ma et al., 2023), knowledge distillation (Gu et al., 2024; Zhang et al., 2024a), and low-rank factorization (Hu et al., 2022; Xu et al., 2024) have enabled models like DistilBERT (Sanh et al., 2019) and TinyBERT (Jiao et al., 2020) to achieve strong performance with fewer parameters. Existing benchmarks, such as GLUE (Wang et al., 2019b) and SuperGLUE (Wang et al., 2019a), primarily evaluate LLMs and lack a focus on SLMs and their performance. This leaves a gap in understanding the trade-offs between efficiency, performance, and sustainability.

### 2.2 Emission-aware Benchmarking on Language Models

The development of LMs demands substantial computational resources, raising environmental concerns. Strubell et al. (Strubell et al., 2019) first quantified LMs’ carbon footprint, and later work (Strubell et al., 2020; Patterson et al., 2021) underscored rising energy demands and sustainability trade-offs. While tools like CodeCarbon (Lottick et al., 2019) and ML CO<sub>2</sub> Impact (Lacoste et al., 2019) enable emissions tracking, benchmarks such as Big-Bench (Authors, 2023) focus largely on performance, neglecting energy impact. Recent work has addressed full-lifecycle emissions. For instance, Luccioni et al. (Luccioni et al., 2023) showed that BLOOM’s total emissions (50.5 tCO<sub>2</sub>) exceeded training emissions due to hardware and idle energy. Hardware choice matters too—T4 to A100 GPU migration can cut emissions by 83% (Liu and Yin, 2024). Fine-tuning also incurs significant cost (Wang et al., 2023). Gowda et al. (Gowda et al., 2023) proposed the Sustainable-Accuracy Metric to balance performance and efficiency. Poddar et al. (Poddar et al., 2025) benchmark LLM inference energy, while Singh et al. (Singh et al., 2024) explore sustainable training and deployment. However, these efforts mainly target LLMs and partial aspects of environmental impact. To our knowledge, SLM-Bench is the first benchmark focused specifically on SLMs with a comprehensive evaluation of both computational and environmental metrics.

## 3 Benchmarking Design

### 3.1 Data Collection

We extensively collect 23 datasets from 11 diverse domains, including common sense, mathematics, physics, news, and legal, among others. These datasets encompass 9 task types, covering reading comprehension, text classification, logical reasoning, sentiment analysis, and more. In total, our dataset collection comprises 799,594 samples, ensuring a well-rounded evaluation framework. Table 1 provides an overview of the collected datasets along with their associated characteristics. Due to space limitations, we provide the details and examples of these datasets in

Appendices A and B, respectively. Our selection of these datasets is motivated by their widespread adoption in previous studies (Myrzakhan et al., 2024), ensuring compatibility and comparability with existing benchmarks. Furthermore, we aim to evaluate SLMs from multiple perspectives, assessing their generalization ability, reasoning capabilities, and robustness across diverse tasks and domains. Integrating datasets from various fields ensures a comprehensive and challenging benchmark that reflects real-world applications.

| Dataset          | #Samples | Domain             | Task                  |
|------------------|----------|--------------------|-----------------------|
| BoolQ            | 15,432   | Open-domain        | Question Answering    |
| ARC-Easy         | 5,876    | Open-domain        | Question Answering    |
| ARC-Challenge    | 2,590    | Open-domain        | Question Answering    |
| OpenBookQA       | 5,957    | Open-domain        | Question Answering    |
| PIQA             | 16,113   | Physics            | Reasoning             |
| Hellaswag        | 10,421   | Common Sense       | Reasoning             |
| WinoGrande       | 44,321   | Common Sense       | Reasoning             |
| CommonsenseQA    | 12,102   | Common Sense       | Reasoning             |
| GSM8k            | 8,034    | Mathematics        | Problem Solving       |
| AQuA             | 99,765   | Mathematics        | Problem Solving       |
| RACE-Middle      | 24,798   | Education          | Reading Comprehension |
| RACE-High        | 26,982   | Education          | Reading Comprehension |
| CoQA             | 127,542  | Open-domain        | Question Answering    |
| e2e_nlg          | 50,321   | Food & Beverage    | Text Generation       |
| viggo            | 9,842    | Video Games        | Text Generation       |
| glue_qnli        | 104,543  | Linguistics        | Question Answering    |
| bc5cdr           | 20,764   | Chemistry          | Recognition           |
| conllpp          | 23,499   | Linguistics        | Recognition           |
| customer_support | 14,872   | Customer Behaviors | Classification        |
| legal            | 49,756   | Legal              | Classification        |
| reuters          | 9,623    | News               | Topic Extraction      |
| covid            | 19,874   | Healthcare         | Sentiment Analysis    |
| drop             | 96,567   | Open-domain        | Reasoning             |

Table 1: Datasets’ Details

### 3.2 Model Selection

We select 15 SLMs for our benchmarking based on three key criteria as follows. (i) **Model Size**: The primary criterion for classification as an SLM is the number of parameters. The LMs must have fewer than 7 billion parameters to qualify as SLMs. (ii) **Popularity & Reputation**: The selected SLMs should be widely recognized and developed by well-known organizations to ensure the impact. (iii) **Open-Source Availability**: The models must be open-source, allowing for transparency, reproducibility, and further research. These criteria ensure a fair, representative, and reproducible benchmarking process, focusing on models that are both accessible and widely used in the research community. Table 2 provides an overview of the selected models. Due to space limitations, we provide the details of these models in Appendix C.

| Model             | #Params (B) | Size (GB) | Year    | Provider      |
|-------------------|-------------|-----------|---------|---------------|
| GPT-Neo-1.3B      | 1.37        | 2.46      | 03/2021 | EleutherAI    |
| Dolly-v2-3B       | 3           | 5.8       | 12/2022 | Databricks    |
| Pythia-2.8B       | 2.8         | 5.5       | 02/2023 | EleutherAI    |
| LLaMA-2-7B        | 6.47        | 13        | 07/2023 | Meta          |
| TinyLlama-1.1B    | 1.1         | 2         | 08/2023 | SUTD          |
| Mistral-7B        | 7           | 13        | 09/2023 | Mistral AI    |
| Zephyr-7B         | 7           | 13.74     | 11/2023 | WebPilot.AI   |
| ShearedLlama-2.7B | 2.7         | 5         | 11/2023 | Princeton NLP |
| Gemma-2B          | 2           | 4.67      | 11/2023 | Google        |
| Phi-1.5B          | 1.42        | 2.84      | 12/2023 | Microsoft     |
| StableLM-3B       | 3           | 6.5       | 12/2023 | Stability AI  |
| Open-LLaMA-3B     | 3           | 6.8       | 06/2024 | OpenLM        |
| Llama-3.2-1B      | 1.24        | 2.47      | 09/2024 | Meta          |
| Phi-3-3.8B        | 3.82        | 2.2       | 01/2025 | Microsoft     |
| Gemma-3-1B        | 1           | 2         | 03/2025 | Google        |

Table 2: SLMs’ Details (sort by release time)

### 3.3 Evaluation

We evaluate an SLM using 11 metrics, covering various aspects of performance and efficiency. These metrics assess accuracy, such as *BLEU*, and computational performance, such as *Runtime*. Our evaluation focuses solely on the fine-tuning process. Since we do not have access to the necessary data for full training, we rely exclusively on pre-trained models. For inference, we did not include runtime comparisons in the paper, as the differences between models were insignificant. Additionally, to measure the resource consumption of SLMs, we incorporate three key metrics: *Cost*, *CO<sub>2</sub> emissions*, and *Energy usage*. This comprehensive evaluation ensures a balanced assessment of both the effectiveness of the model and its environmental and financial impact. To measure resource consumption, we use the APIs of the experimental server to measure both FLOPs and cost. Specifically, we conducted experiments by renting a **lightning.ai**<sup>1</sup> server and recorded the deducted amount from our account balance as the cost. Additionally, we used a built-in function of the same platform to measure FLOPs. To estimate CO<sub>2</sub> emissions, we use the ML CO<sub>2</sub> package<sup>2</sup>, calling its built-in function. For energy consumption, we use the Zeus package<sup>3</sup> in a similar manner. It is important to note that FLOP, costs, CO<sub>2</sub> emissions, and energy consumption vary across different hardware configurations. If end-users run the models on a local server, FLOPs can be measured using the cal\_flops library. The

<sup>1</sup><https://lightning.ai/>

<sup>2</sup><https://mlco2.github.io/impact/>

<sup>3</sup><https://ml.energy/zeus/>



cost can be estimated by multiplying energy consumption, runtime, and electricity price. Table 3 provides an overview of the evaluation metrics. Due to space limitations, we provide the details of these metrics in Appendix D.

| Metrics         | Evaluation  | Task   | Dataset                              |
|-----------------|-------------|--|--------------------------------------|
| Accuracy        | Correctness | Question Answering<br>Classification<br>Recognition<br>Reasoning<br>Problem Solving<br>Reading Comprehension | All except [e2e_nlg, viggo, reuters] |
| F1 Score        | Correctness | Question Answering<br>Classification<br>Recognition<br>Reasoning<br>Problem Solving<br>Reading Comprehension | All except [e2e_nlg, viggo, reuters] |
| BLEU            | Correctness | Text Generation<br>Topic Extraction  | e2e_nlg, viggo, reuters              |
| ROUGE           | Correctness | Text Generation<br>Topic Extraction  | e2e_nlg, viggo, reuters              |
| METEOR          | Correctness | Text Generation<br>Topic Extraction  | e2e_nlg, viggo, reuters              |
| Perplexity      | Correctness | Text Generation<br>Topic Extraction  | e2e_nlg, viggo, reuters              |
| Runtime         | Computation | All  | All                                  |
| FLOP            | Computation | All  | All                                  |
| Cost            | Consumption | All  | All                                  |
| CO <sub>2</sub> | Consumption | All  | All                                  |
| Energy          | Consumption | All  | All                                  |

Table 3: Metrics’ Details

### 3.4 Benchmarking Pipeline

To enhance extensibility and reproducibility, we design a unified process pipeline for benchmarking, consisting of 7 key modules. The *Universal Data Loader* ensures consistency by converting datasets of different formats into a unified structure. The *Preprocessing* module then refines the data by trimming, removing special symbols, and applying necessary transformations. Once the data is prepared, the *Calling* module manages the execution of SLMs and tasks, enabling flexibility where a single SLM can be tested on multiple tasks and vice versa. After inference, the output undergoes further refinement through the *Post-processing* module before moving to the *Evaluation* module, which applies appropriate metrics to assess model performance. Finally, the *Report* module compiles results and visualizations, providing insights into the model’s effectiveness. Additionally, the *Logging* module is integrated throughout the pipeline to record all events, enabling better traceability, debugging, and transparency. This modular design allows for scalability, flexibility, and ease of adaptation, making it

well-suited for benchmarking and future extensions. Figure 2 illustrates the proposed pipeline.

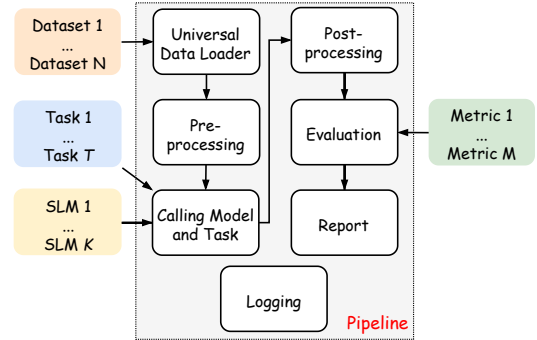


Figure 2: Benchmarking Pipeline

### 3.5 Ranking Methodology

We propose a ranking method for SLMs based on their performance across multiple datasets and evaluation metrics. This method counts how often each model ranks first, second, or third in different experimental settings. Specifically, let  $K$  be the number of SLMs,  $N$  the number of datasets,  $T$  the number of tasks, and  $M$  the number of evaluation metrics. For each model  $k$ , we count the number of times it achieves the best (gold medal), second-highest (silver medal), and third-highest (bronze medal) performance across all  $K \times N \times T \times M$  cases. This approach provides a straightforward yet effective way to assess overall model performance by considering rankings across diverse conditions rather than relying on a single aggregated metric. By aggregating the detailed benchmark results into a comprehensive summary, we aim to make insights more accessible to end-users, allowing users to quickly select models based on three major criteria: accuracy, efficiency, or energy consumption.

## 4 Experiments

### 4.1 Implementation Details

We conduct our experiments on [lightning.ai](https://lightning.ai), a cloud-based platform designed as a development studio for building, training, and deploying AI models. Lightning AI offers support for various hardware configurations, allowing flexibility in experimentation. We conduct evaluations across four hardware configurations: two server-grade and two edge-device setups. The server configu-

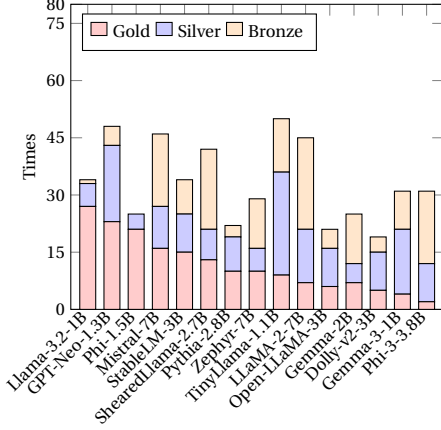


Figure 3: Overall Results

rations use NVIDIA L4 and A10 GPUs, while the edge-device configurations use NVIDIA Jetson Orin AGX with 16GB and 64GB memory, respectively. Due to space constraints, the main paper reports results only on the NVIDIA L4 GPU. Results for the other configurations are provided on the Leaderboard. Furthermore, while the magnitudes of the results vary on different hardware configurations, the relative ranking among the SLMs remains consistent. In addition, we implement the benchmarking pipeline (see Figure 2) by using Python 3.10, Numpy 1.24, Pandas 1.5, PyTorch 2.0, Sklearn 1.2 and Zeus-ML 0.7.0.

## 4.2 Hyperparameter Settings

We select hyperparameters based on recommendations from various sources, including original research papers, official code repositories, and Hugging Face<sup>4</sup> model hubs, which often provide well-tuned configurations for strong performance. When specific values are unavailable for a given model-dataset pair, we apply a systematic fine-tuning strategy using a validation set to iteratively optimize performance. Our hyperparameter tuning process includes the following steps: (1) defining appropriate search ranges and (2) conducting a random search over the defined space. Specifically, we vary *learning\_rate* from 1e-6 to 1e-4; *batch\_size* among 2, 4, 8, 16, 32, 64, 128; fine-tuning *epochs* among 2, 4, 6, 8, 10; *LoRA\_rank* among 2, 4, 6, 8, 10; and dropout probability among 0.1, 0.2, 0.3, 0.4, 0.5. This approach ensures a fair and consistent evaluation

<sup>4</sup><https://huggingface.co/>

across all models and datasets.

## 4.3 Overall Results

We present the overall results in Figure 3, which visualizes the ranking of each SLM across all datasets and evaluation metrics. The models are sorted from left to right based on the number of gold medals they have achieved. Our analysis reveals that Llama-3.2-1B outperforms the other SLMs, securing the highest number of gold medals. This indicates that it consistently delivers top-tier performance across a diverse range of evaluations. Additionally, GPT-Neo-1.3B emerges as the runner-up in terms of gold medal count, further demonstrating strong performance. Following closely, Phi-1.5B performs competitively, securing the third-highest number of gold medals. This model exhibit strong results, often excelling in specific datasets or metrics. Meanwhile, Mistral-7B, TinyLlama-1.1B and LLaMA-2-7B, while not securing the most gold medals, frequently appear in the top-three rankings. This suggests that these models maintain a high level of robustness and consistency across various tasks, even if they do not always achieve the top position.

Furthermore, TinyLlama-1.1B and LLaMA-2-7B appear in the middle of the rankings, securing a moderate number of gold medals while frequently earning silver and bronze medals. Although they do not dominate in terms of gold medal achievements, their balanced performance across different evaluation criteria suggests that they remain competitive across various tasks. Their ability to accumulate a significant number of medals overall indicates that they can serve as reliable alternatives to the top-performing models, especially in scenarios where consistency across multiple benchmarks is valued. Meanwhile, Dolly-v2-3B, Gemma-3-1B, and Phi-3-3.8B rank toward the lower end of the leaderboard, achieving the fewest gold medals among the evaluated models. While their performance is less dominant, they still manage to secure some silver and bronze medals, indicating that they exhibit strengths in certain areas. These results highlight the varying capabilities of SLMs and the potential trade-offs when selecting a model

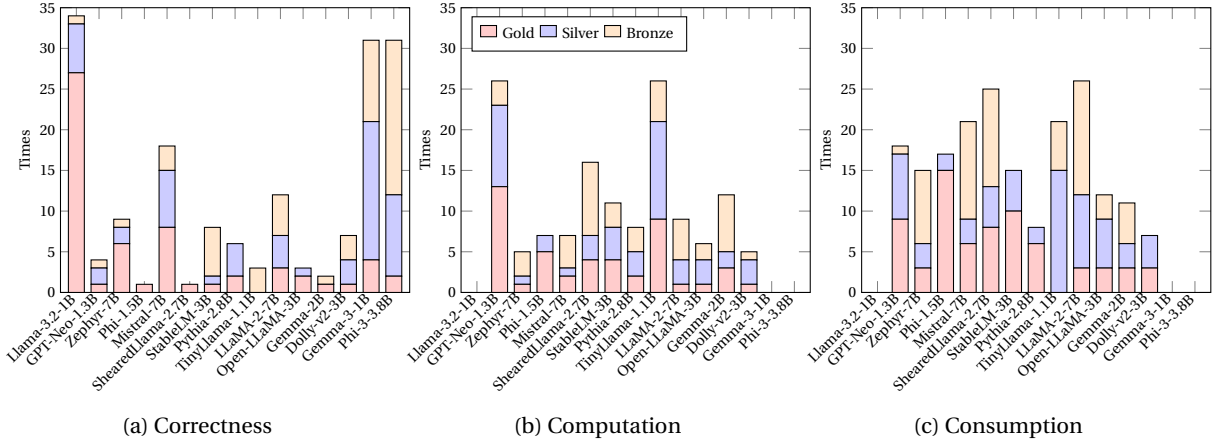


Figure 4: Taxonomy Results

for specific applications. Appendix E further discusses the metric contribution to medals in 15 models. Further, Appendix F presents the inference cost.

#### 4.4 Evaluation Taxonomy

We categorize the evaluation metrics into three distinct types: correctness, computation, and consumption (see Table 3). Figure 4 presents the performance results for each evaluation type, highlighting the strengths of different SLMs across these dimensions.

In terms of correctness, Llama-3.2-1B earns the most gold medals, making it the most accurate SLM in our evaluation. Mistral-7B follows closely, with Gemma-3-1B and Phi-3-3.8B also frequently ranking in the top three, reflecting their consistent output quality.

For computational efficiency, GPT-Neo-1.3B leads with the highest number of gold medals, suggesting strong performance in processing speed and resource usage. TinyLlama-1.1B and ShearedLlama-2.7B also rank highly, demonstrating notable efficiency across tasks.

In terms of resource consumption, Phi-1.5B stands out as the most energy-efficient model. StableLM-3B and GPT-Neo-1.3B share the second-highest number of gold medals, while LLaMA-2.7B and ShearedLlama-2.7B frequently appear among the top performers, highlighting their sustainable design.

Although computation and energy consumption are often correlated, they are not equivalent. Some models use more energy to achieve faster

runtimes, while others with similar compute may be less efficient due to non-parallelizable operations and architectural bottlenecks.

We observe that correctness does not strongly correlate with computation or consumption. This is because accuracy depends not only on model size, but also on the quality and diversity of pre-training data. Similarly, consumption and computational cost are influenced by more than just model size—factors like model architecture, parallelization efficiency, and computational complexity play a significant role. For example, Llama-3.2-1B, despite its small size, achieves the highest accuracy but performs poorly in computation and energy consumption—an unexpected yet insightful outcome.

#### 4.5 Performance Trade-off

We visualize the performance trade-offs of SLMs using Kivi charts. Our evaluation considers three key performance aspects: correctness, computation, and consumption. Initially, we focus on the number of gold medals each SLM has achieved. To enhance readability, we select five top-performing SLMs from previous experiments: Llama-3.2-1B, GPT-Neo-1.3B, Zephyr-7B, Phi-1.5B, and Mistral-7B. Figure 5 illustrates the performance trade-offs among these models.

Our observations reveal that Llama-3.2-1B excels in correctness but falls short in computation and consumption efficiency. In contrast, Phi-1.5B demonstrates the highest efficiency in consumption but lags in correctness.

Next, GPT-Neo-1.3B achieves the best performance in computation but also lags in correctness. Mistral-7B maintains a balanced performance across all three metrics, making it a strong candidate for scenarios requiring an all-around solution.

Next, instead of solely considering the number of gold medals, we adopt a score-based evaluation approach that accounts for all gold, silver, and bronze medals. Specifically, we assign a weighted score to each medal type: each gold medal contributes 3 points, each silver medal contributes 2 points, and each bronze medal contributes 1 point. We then compute the total score for each SLM across the three evaluation categories by summing the respective scores. This method provides a more nuanced assessment of model performance, capturing relative strengths beyond just the highest achievements. To maintain consistency and readability, we again focus on the five top-performing SLMs identified in the previous experiment. Figure 6 illustrates the performance trade-offs among these models under the score-based evaluation framework.

Our observations remain consistent in that Llama-3.2-1B continues to excel in correctness while exhibiting weaker performance in computation and consumption efficiency. However, the score-based evaluation reveals additional insights. Notably, Mistral-7B outperforms Phi-1.5B and Zephyr-7B across all three evaluation metrics, indicating that it provides a more balanced trade-off between accuracy and efficiency. Furthermore, GPT-Neo-1.3B maintains well-rounded performance across correctness, computation, and consumption, reinforcing its suitability for scenarios where an all-purpose model is desirable.

#### 4.6 Discussion

After conducting extensive experiments and analyzing the results, we can derive several key end-user recommendations when selecting an appropriate SLM. There are clear trade-offs among three key dimensions: correctness, computational efficiency, and resource consumption. If accuracy is the primary goal, Llama-3.2-1B is a strong choice, consistently ranking highest in correctness metrics. However, this comes with

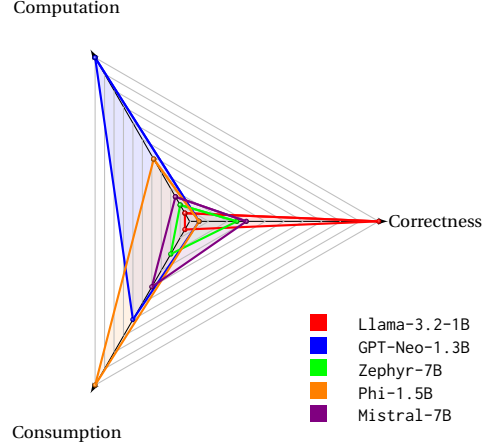


Figure 5: Performance Trade-off, only Gold Medals

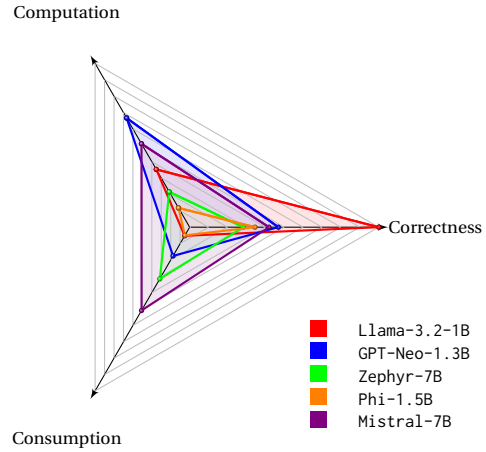


Figure 6: Performance Trade-off, Score-based Evaluation

increased computational and energy costs. For scenarios requiring fast and efficient execution, GPT-Neo-1.3B offers superior runtime performance, making it suitable for latency-sensitive tasks. If energy efficiency and sustainability are critical, Phi-1.5B is the most resource-friendly option, ideal for deployment on low-power or edge devices. For applications needing a balance across all three criteria, Mistral-7B performs reliably and consistently, making it a versatile, well-rounded choice. Finally, the choice of SLM should be guided by specific application requirements, as different models offer varying strengths and weaknesses that may influence real-world deployment decisions.



## 5 Conclusion

We introduce SLM-Bench, a comprehensive benchmark for evaluating the environmental impact of SLMs. It provides critical insights to guide the selection, optimization, and deployment of models, helping researchers and practitioners balance accuracy, efficiency, and sustainability—especially in resource-constrained settings. To support future research, SLM-Bench includes an open-source, extensible pipeline for continuous integration. In future work, we plan to incorporate additional SLMs and explore a wider range of hardware settings. Additionally, we aim to enhance the accuracy of energy consumption and CO<sub>2</sub> emission measurements by utilizing sensor-equipped devices. We also plan to incorporate instruction-following capabilities as a distinct task dimension, extending the benchmark’s coverage of real-world use cases.

## 6 Limitations

Although SLM-Bench provides a solid evaluation of SLMs, it has limitations. First, environmental metrics like energy consumption, CO<sub>2</sub> emissions, and runtime depend heavily on the hardware used. So far, we have only tested 4 configurations and plan to include more in future work. Second, energy consumption and CO<sub>2</sub> emissions are currently estimated using standardized formulas rather than real-time measurements. We aim to improve this by using sensor-equipped devices to capture actual energy usage and emissions.

## 7 Broader Impact

SLM-Bench promotes the development and deployment of efficient, sustainable, and accessible AI by focusing on SLMs. By evaluating models across accuracy, computation, and energy consumption, our benchmark helps users make informed, responsible choices—especially in resource-constrained environments. Our inclusion of environmental metrics raises awareness of AI’s carbon footprint and supports more sustainable practices. By making the benchmark publicly available and regularly updated, we aim to drive progress in green AI and practical model deployment across both academia and industry.

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## **Appendix**

### **A Datasets Details**

Table [A1](#) presents a comprehensive overview of the benchmark datasets used in this study, including their key characteristics such as dataset size, dataset domains, venues, and task objectives. This detailed comparison helps contextualize their relevance and challenges in the broader scope of our analysis

### **B Datasets Examples**

Figures [A1–A23](#) provide representative examples from the benchmark datasets used in this study. We randomly sample two instances from each dataset, showing the variety of question formats, input structures, and answer types present in these benchmarks. These examples provide insight into the challenges posed by each dataset and highlight the differences in their underlying tasks.

|   |
|---|
| <b>Example 1</b>  |
| <p><b>Question:</b> Can dogs see color?</p> <p><b>Passage:</b> Dogs can see colors, but not as vividly as humans. Their color vision is similar to that of a person with red-green color blindness. They primarily see shades of blue and yellow.</p> <p><b>Answer:</b> true</p>  |
| <b>Example 2</b>  |
| <p><b>Question:</b> Is Mount Everest the tallest mountain in the world?</p> <p><b>Passage:</b> Mount Everest, located in the Himalayas, is the highest mountain above sea level, with a peak reaching 8,848.86 meters. However, if measuring from base to peak, Mauna Kea in Hawaii is technically the tallest mountain.</p> <p><b>Answer:</b> true</p> |

Figure A1: Examples from **BoolQ**

|   |
|---|
| <b>Example 1</b>  |
| <p><b>Question:</b> Which planet is known as the Red Planet?</p> <p><b>Options:</b> [Mercury, Venus, Earth, Mars]</p> <p><b>Answer:</b> Mars</p>                  |
| <b>Example 2</b>  |
| <p><b>Question:</b> What do plants absorb from the soil?</p> <p><b>Options:</b> [Oxygen, Nutrients, Carbon dioxide, Sunlight]</p> <p><b>Answer:</b> Nutrients</p> |

Figure A2: Examples from **ARC-Easy**

|  |
|--|
| <b>Example 1</b>   |
| <p><b>Question:</b> Why do stars appear to twinkle in the night sky?</p> <p><b>Options:</b> [ Because stars themselves are flickering, Due to the movement of air in the Earth's atmosphere, Because of their distance from Earth, Due to changes in their brightness ]</p> <p><b>Answer:</b> Due to the movement of air in the Earth's atmosphere</p> |
| <b>Example 2</b>   |
| <p><b>Question:</b> Which of the following substances is a poor conductor of electricity?</p> <p><b>Options:</b> [Silver, Copper, Rubber, Iron]</p> <p><b>Answer:</b> Rubber</p>   |

Figure A3: Examples from **ARC-Challenge**

| No | Dataset                 | #Samples | #Tokens | Domain             | Task                  | Venues      | Description   |
|----|-------------------------|----------|---------|--------------------|-----------------------|-------------|---|
| 1  | <b>BoolQ</b>            | 15,432   | 3M      | Common Sense       | Question Answering    | NAACL 2019  | A yes/no question-answering dataset where each question requires reasoning over a short passage (Clark et al., 2019).                             |
| 2  | <b>ARC-Easy</b>         | 5,876    | 1.8M    | Common Sense       | Question Answering    | arXiv       | A subset of the AI2 Reasoning Challenge with straightforward grade-school science questions (Clark et al., 2018).                                 |
| 3  | <b>ARC-Challenge</b>    | 2,590    | 1.5M    | Common Sense       | Question Answering    | arXiv       | A more difficult subset of ARC with questions requiring reasoning and external knowledge (Clark et al., 2018).                                    |
| 4  | <b>OpenBookQA</b>       | 5,957    | 1M      | Common Sense       | Question Answering    | EMNLP 2018  | A multiple-choice question-answering dataset that requires knowledge from a small "open book" of science facts (Mihaylov et al., 2018).           |
| 5  | <b>PIQA</b>             | 16,113   | 1.6M    | Physics            | Reasoning             | AAAI 2020   | A dataset for physical commonsense reasoning, testing knowledge of how objects are used in everyday situations (Bisk et al., 2020).               |
| 6  | <b>Hellaswag</b>        | 10,421   | 10M     | Common Sense       | Reasoning             | ACL 2019    | A dataset for commonsense reasoning and next-sentence prediction with adversarially mined, plausible distractors (Zellers et al., 2019).          |
| 7  | <b>WinoGrande</b>       | 44,321   | 5M      | Common Sense       | Reasoning             | AAAI 2020   | A large-scale dataset for pronoun resolution tasks, inspired by the Winograd Schema Challenge (Sakaguchi et al., 2020).                           |
| 8  | <b>CommonsenseQA</b>    | 12,102   | 1.8M    | Common Sense       | Reasoning             | ICONIP 2023 | A multiple-choice dataset testing broad commonsense knowledge using questions based on ConceptNet (Zhang and Li, 2023).                           |
| 9  | <b>GSM8k</b>            | 8,034    | 2M      | Math               | Problem Solving       | arXiv       | A dataset of grade-school math word problems designed to evaluate problem-solving abilities (Liu et al., 2023).                                   |
| 10 | <b>AQuA</b>             | 99,765   | 3M      | Math               | Problem Solving       | VLDB 2023   | A dataset with multiple-choice questions Algebraic Word Problems requiring reasoning over numeric expressions (Peng et al., 2023).                |
| 11 | <b>RACE-Middle</b>      | 24,798   | 7M      | Education          | Reading Comprehension | EMNLP 2017  | A subset of the RACE dataset with English reading comprehension questions from middle school exams (Lai et al., 2017).                            |
| 12 | <b>RACE-High</b>        | 26,982   | 10M     | Education          | Reading Comprehension | EMNLP 2017  | A subset of RACE with more challenging reading comprehension questions from high school exams (Lai et al., 2017).                                 |
| 13 | <b>CoQA</b>             | 127,542  | 5M      | Common Sense       | Question Answering    | LREC 2022   | A conversational question-answering dataset where each question depends on the context of prior dialogue (Brabant et al., 2022).                  |
| 14 | <b>e2e_nlg</b>          | 50,321   | 600K    | Food & Beverage    | Text Generation       | INLG 2018   | A dataset for end-to-end natural language generation for restaurant-related dialogue (Dusek et al., 2018).  |
| 15 | <b>viggo</b>            | 9,842    | 500K    | Video Games        | Text Generation       | INLG 2019   | A dataset for video game-related natural language generation, mapping structured input into natural language descriptions (Juraska et al., 2019). |
| 16 | <b>glue_qnli</b>        | 104,543  | 6M      | Linguistics        | Question Answering    | arXiv       | A question-answering dataset reformulated as a binary classification task for sentence pair entailment (Shu and Du, 2024).                        |
| 17 | <b>bc5cdr</b>           | 20,764   | 5M      | Chemistry          | Recognition           | ICIMMI 2023 | A biomedical dataset for disease and chemical entity recognition, derived from PubMed articles (Gupta et al., 2023).                              |
| 18 | <b>conllpp</b>          | 23,499   | 1.2M    | Linguistics        | Recognition           | EMNLP 2023  | An enhanced version of the CoNLL-2003 dataset for named entity recognition (Al-Shaibani and Ahmad, 2023).   |
| 19 | <b>customer_support</b> | 14,872   | 300K    | Customer Behaviors | Classification        | CODS 2022   | A dataset of customer support interactions for intent classification and response generation (Prabhu et al., 2022).                               |
| 20 | <b>legal</b>            | 49,756   | 5M      | Legal              | Classification        | arXiv       | A legal domain dataset for natural language processing tasks such as legal document classification and contract analysis (Wan et al., 2019).      |
| 21 | <b>reuters</b>          | 9,623    | 2M      | News               | Topic Extraction      | JMLR 2004   | A classic dataset for text classification, often used in topic modeling and news categorization (Lewis et al., 2004).                             |
| 22 | <b>covid</b>            | 19,874   | 3M      | Healthcare         | Sentiment Analysis    | TCSS 2021   | A dataset containing COVID-19-related texts from social media posts, typically used for sentiment analysis (Naseem et al., 2021).                 |
| 23 | <b>drop</b>             | 96,567   | 4M      | Common Sense       | Reasoning             | NAACL 2019  | A reading comprehension dataset requiring discrete reasoning over paragraphs, such as arithmetic operations (Dua et al., 2019).                   |

Table A1: Dataset Details

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| <b>Example 1</b>   |
| <p><b>Question:</b> What is the primary function of the root in a plant?</p> <p><b>Options:</b> [ To store sunlight for later use, To absorb water and nutrients, To produce oxygen, To perform photosynthesis ]</p> <p><b>Answer:</b> To absorb water and nutrients</p> |
| <b>Example 2</b>   |
| <p><b>Question:</b> Why do objects fall to the ground when dropped?</p> <p><b>Options:</b> [ Because of magnetism, Due to the force of gravity, Because the air pushes them down, Due to Earth's rotation ]</p> <p><b>Answer:</b> Due to the force of gravity</p>        |

Figure A4: Examples from **OpenBookQA**

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| <b>Example 1</b>   |
| <p><b>Question:</b> What is the best way to move a heavy box across a smooth floor?</p> <p><b>Options:</b> [ Push it while keeping it flat on the ground, Lift it and carry it, Drag it using a rope tied to the bottom, Kick it repeatedly until it moves ]</p> <p><b>Answer:</b> Push it while keeping it flat on the ground</p> |
| <b>Example 2</b>   |
| <p><b>Question:</b> How can you efficiently dry wet clothes indoors?</p> <p><b>Options:</b> [ Lay them flat on a table, Hang them near a heat source or a fan, Roll them into a ball and leave them overnight, Put them in a plastic bag ]</p> <p><b>Answer:</b> Hang them near a heat source or a fan</p>                         |

Figure A5: Examples from **PIQA**

|  |
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| <b>Example 1</b>   |
| <p><b>Context:</b> A person is slicing a tomato on a cutting board.</p> <p><b>Ending options:</b> [ The person places the tomato slices on a plate., The person throws the tomato slices into the trash. ]</p> <p><b>Correct ending:</b> The person places the tomato slices on a plate.</p>               |
| <b>Example 2</b>   |
| <p><b>Context:</b> A man is playing a guitar on stage during a concert.</p> <p><b>Ending options:</b> [ The audience claps and cheers after his performance., The man stops playing and leaves the stage silently. ]</p> <p><b>Correct ending:</b> The audience claps and cheers after his performance</p> |

Figure A6: Examples from **Hellaswag**



**Example 1**

**Sentence:** The trophy doesn't fit into the brown suitcase because it is too large.  
**Question:** What is too large? **Options:** [ trophy, suitcase ]  
**Answer:** trophy

**Example 2**

**Sentence:** The cat chased the mouse because it was hungry.  
**Question:** What was hungry? **Options:** [ cat, mouse ]  
**Answer:** cat

Figure A7: Examples from **WinoGrande**

**Example 1**

**Question:** Where would you find a chandelier?  
**Options:** [ ceiling, floor, wall, table, window ]  
**Answer:** ceiling

**Example 2**

**Question:** What do people use to keep their hair dry while swimming?  
**Options:** [ swim cap, goggles, flippers, towel, sunscreen ]  
**Answer:** swim cap

Figure A8: Examples from **CommonsenseQA**

**Example 1**

**Question:** If a train travels at a speed of 60 miles per hour, how long will it take to travel 180 miles?  
**Answer:** 3 hours

**Example 2**

**Question:** A bookstore sold 120 books in a week. If they sold 30 books each day from Monday to Thursday, how many books did they sell on Friday?  
**Answer:** 0 books

Figure A9: Examples from **GSM8k**

**Example 1**

**Question:** If a car's fuel efficiency is 25 miles per gallon and the car has a 15-gallon tank, how far can the car travel on a full tank?  
**Options:** [ 300 miles, 350 miles, 375 miles, 400 miles ]  
**Answer:** 375 miles

**Example 2**

**Question:** A rectangle has a length of 10 cm and a width of 5 cm. What is the area of the rectangle?  
**Options:** [ 15 cm<sup>2</sup>, 30 cm<sup>2</sup>, 50 cm<sup>2</sup>, 100 cm<sup>2</sup> ]  
**Answer:** 50 cm<sup>2</sup>

Figure A10: Examples from **AQuA**

### Example 1

**Article:** There is not enough oil in the world now. As time goes by, it becomes less and less, so what are we going to do when it runs out? Perhaps we will have to go back to using horses, carriages and bicycles.

**Question:** According to the passage, which of the following statements is TRUE?

**Options:** [ There is more petroleum than we can use now., Trees are needed for some other things besides making gas., We got electricity from ocean tides in the old days., Gas wasn't used to run cars in the Second World War. ]

**Answer:** Gas wasn't used to run cars in the Second World War.

### Example 2

**Article:** Schoolgirls have been wearing such short skirts at Paget High School in Branston that they've been ordered to wear trousers instead.

**Question:** The girls at Paget High School are not allowed to wear skirts because.

**Options:** [ short skirts give people the impression of sexualisation, short skirts are too expensive for parents to afford, the headmaster doesn't like girls wearing short skirts, the girls wearing short skirts will be at the risk of being laughed at ]

**Answer:** short skirts give people the impression of sexualisation.

Figure A11: Examples from **RACE-Middle**

### Example 1

**Article:** Next eliminate most of their planets; they are either too far from or too close to their suns. Then eliminate all those planets which are not the same size and weight as the earth. Finally, remember that the proper conditions do not necessarily mean that life actually does exist on a planet. It may not have begun yet, or it may have already died out. This process of elimination seems to leave very few planets on which earthlike life might be found.

**Question:** What is the main idea of the passage?

**Options:** [ The universe is full of planets., Life is rare in the universe., Earth is unique in the universe., The conditions for life are complex. ]

**Answer:** Life is rare in the universe.

### Example 2

**Article:** Some kids listen to music, watch TV or use the phone while doing their homework. 'It's important to make sure that you can stop and concentrate on one thing deeply,' says Rideout. With new and exciting devices hitting stores every year, keeping technology use in check is more important than ever. 'Kids should try,' adds Rideout. 'But parents might have to step in sometimes.'

**Question:** Which of the following is an example of multitasking according to the passage?

**Options:** [ Watching TV while using the computer., Talking on the phone while staying with others., Playing video games on the Internet., Listening to music while relaxing. ]

**Answer:** Watching TV while using the computer.

Figure A12: Examples from **RACE-High**

|  |
|--|
| <b>Example 1</b>   |
| <p><b>Passage:</b> Once upon a time, there was a little girl named Goldilocks. She went for a walk in the forest. Pretty soon, she came upon a house. She knocked and, when no one answered, she walked right in.</p> <p><b>Turns:</b> [ <i>Question:</i> What was the girl's name? <i>Answer:</i> Goldilocks , <i>Question:</i> Where did she go for a walk? <i>Answer:</i> In the forest ]</p> |
| <b>Example 2</b>   |
| <p><b>Passage:</b> John took his dog Max to the vet because Max was not feeling well. The vet examined Max and gave him some medicine.</p> <p><b>Turns:</b> [ <i>Question:</i> Why did John take Max to the vet? <i>Answer:</i> Because Max was not feeling well , <i>Question:</i> What did the vet do? <i>Answer:</i> Examined Max and gave him some medicine ]</p>                            |

Figure A13: Examples from **CoQA**

|  |
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| <b>Example 1</b>   |
| <p><b>Meaning representation:</b> [ <i>name:</i> The Eagle, <i>eat_type:</i> restaurant, <i>food:</i> French, <i>price_range:</i> high, <i>customer_rating:</i> 5 out of 5, <i>near:</i> Riverside ]</p> <p><b>Human reference:</b> The Eagle is a highly rated French restaurant near Riverside with a high price range.</p>                            |
| <b>Example 2</b>   |
| <p><b>Meaning representation:</b> [ <i>name:</i> The Golden Curry, <i>eat_type:</i> pub, <i>food:</i> Indian, <i>price_range:</i> low, <i>customer_rating:</i> 3 out of 5, <i>family_friendly:</i> yes ]</p> <p><b>Human reference:</b> The Golden Curry is a family-friendly Indian pub with a low price range and a customer rating of 3 out of 5.</p> |

Figure A14: Examples from **e2e\_nlg**

|   |
|---|
| <b>Example 1</b>  |
| <p><b>Meaning representation:</b> [ <i>name:</i> Super Mario World, <i>release_year:</i> 1990, <i>esrb:</i> E (for Everyone), <i>rating:</i> excellent, <i>genres:</i> [ platformer ], <i>player_perspective:</i> [ side view ], <i>has_multiplayer:</i> yes, <i>platforms:</i> [ Nintendo ] ]</p> <p><b>Human reference:</b> Super Mario World is an excellent platformer game that is played in the side view. It was released in 1990 on Nintendo and is rated E (for Everyone). It can be played multiplayer.</p> |
| <b>Example 2</b>  |
| <p><b>Meaning representation:</b> [ <i>name:</i> The Elder Scrolls V: Skyrim, <i>release_year:</i> 2011, <i>esrb:</i> M (for Mature), <i>genres:</i> [ adventure, role-playing ] ]</p> <p><b>Human reference:</b> The Elder Scrolls V: Skyrim is an adventure RPG that came out in 2011. It's rated M (for Mature).</p>   |

Figure A15: Examples from **viggo**

|  |
|--|
| <b>Example 1</b>   |
| <b>Question:</b> What is the capital of France?<br><b>Sentence:</b> Paris is the capital and most populous city of France.<br><b>Label:</b> entailment |
| <b>Example 2</b>   |
| <b>Question:</b> Who wrote 'Pride and Prejudice'?<br><b>Sentence:</b> 'Pride and Prejudice' is a novel by Jane Austen.<br><b>Label:</b> entailment     |

Figure A16: Examples from **glue\_qnli**

|  |
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| <b>Example 1</b>   |
| <b>Text:</b> Aspirin is commonly used to reduce fever.<br><b>Entities:</b> [ <i>entity:</i> Aspirin, <i>type:</i> Chemical, <i>start:</i> 0, <i>end:</i> 7 ]                   |
| <b>Example 2</b>   |
| <b>Text:</b> Hypertension can lead to serious health complications.<br><b>Entities:</b> [ <i>entity:</i> Hypertension, <i>type:</i> Disease, <i>start:</i> 0, <i>end:</i> 11 ] |

Figure A17: Examples from **bc5cdr**

|  |
|--|
| <b>Example 1</b>   |
| <b>Sentence:</b> Barack Obama was born in Hawaii.<br><b>Entities:</b> [ [ <i>entity:</i> Barack Obama, <i>type:</i> PERSON, <i>start:</i> 0, <i>end:</i> 12 ], [ <i>entity:</i> Hawaii, <i>type:</i> LOCATION, <i>start:</i> 25, <i>end:</i> 31 ] ]  |
| <b>Example 2</b>   |
| <b>Sentence:</b> Apple Inc. is headquartered in Cupertino, California.<br><b>Entities:</b> [ [ <i>entity:</i> Apple Inc., <i>type:</i> ORGANIZATION, <i>start:</i> 0, <i>end:</i> 9 ], [ <i>entity:</i> Cupertino, <i>type:</i> LOCATION, <i>start:</i> 29, <i>end:</i> 38 ], [ <i>entity:</i> California, <i>type:</i> LOCATION, <i>start:</i> 40, <i>end:</i> 50 ] ] |

Figure A18: Examples from **conllpp**

|   |
|---|
| <b>Example 1</b>  |
| <b>Query:</b> How can I reset my password?<br><b>Category:</b> Account Management       |
| <b>Example 2</b>  |
| <b>Query:</b> What is the status of my order #12345?<br><b>Category:</b> Order Tracking |

Figure A19: Examples from **customer\_support**



|  |
|--|
| <b>Example 1</b>   |
| <b>Text:</b> The defendant was found guilty of theft under Section 378 of the Penal Code.<br><b>Category:</b> Criminal Law |
| <b>Example 2</b>   |
| <b>Text:</b> The contract was terminated due to a breach of the confidentiality clause.<br><b>Category:</b> Contract Law   |

Figure A20: Examples from **legal**

|  |
|--|
| <b>Example 1</b>   |
| <b>Headline:</b> Oil prices rise as OPEC agrees to cut production.<br><b>Topics:</b> [ Economy, Energy ]     |
| <b>Example 2</b>   |
| <b>Headline:</b> Tech stocks rally amid strong quarterly earnings.<br><b>Topics:</b> [ Technology, Markets ] |

Figure A21: Examples from **reuters**

|   |
|---|
| <b>Example 1</b>  |
| <b>Text:</b> The new vaccine has shown promising results in early trials.<br><b>Sentiment:</b> positive     |
| <b>Example 2</b>  |
| <b>Text:</b> Lockdown measures have been extended due to rising case numbers.<br><b>Sentiment:</b> negative |

Figure A22: Examples from **covid**

|   |
|---|
| <b>Example 1</b>  |
| <b>Passage:</b> In 1995, the population of the city was 1.2 million. By 2005, it had increased to 1.5 million.<br><b>Question:</b> What was the increase in population from 1995 to 2005?<br><b>Answer:</b> 300,000 |
| <b>Example 2</b>  |
| <b>Passage:</b> The team scored 24 points in the first half and 30 points in the second half.<br><b>Question:</b> What was the total score for the team?<br><b>Answer:</b> 54 points                                |

Figure A23: Examples from **drop**

## C Models

Table A2 provides detailed information on SLMs in this study, including their providers, licenses, parameter sizes, model sizes, training time, and training performance. We observe that Llama-3.2-1B, Phi-3-3.8B, and Gemma-3-1B possess extended context lengths and were pre-trained on more extensive corpora, which appears to strongly influence their correctness.

## D Metrics Details

Table A3 provides detailed explanations of the metrics used in our evaluation framework. We categorize our metrics into three main groups: correctness evaluation, computation evaluation, and consumption evaluation.

## E Expanded Analysis of Metric Contributions to Medals

For each model, gold medals indicate the best performance using specific metrics. Some models show dominance in a single metric, suggesting specialization, while others maintain a balanced distribution of Gold medals across multiple metrics, indicating versatility. Models with more evenly distributed Gold, Silver, and Bronze medals across different criteria tend to be more well-rounded, offering strong performance without extreme specialization.

The Silver and Bronze medal distributions further refine this understanding. A model that consistently earns Silver in multiple metrics suggests strong overall performance but is slightly outperformed by one or more competitors in specific cases. Conversely, a model with many Bronze medals may still be efficient but is frequently ranked below two other models. This suggests that while it is competitive, it does not lead to any single criterion.

Among the expanded selection of models, differences in trade-offs become more apparent. Some models score highly in cost efficiency but rank lower in computational complexity, indicating that they are affordable but require significant processing resources. Others achieve substantial results in energy efficiency while being slightly less cost-effective, making them preferable in energy-conscious environments. The ex-

panded dataset also provides insights into the impact of computational complexity, where models that rank lower in this criterion might still perform well in other categories, balancing out the trade-offs.

By examining a more extensive set of models, this analysis helps refine decision-making for different use cases. Whether the goal is to prioritize training speed, minimize cost, reduce energy consumption, or optimize computational efficiency, this breakdown provides clear guidance on which models align best with specific operational priorities. The broader dataset ensures that model selection is not limited to a few top-performing options. Instead, it considers a wider range of competitive alternatives, each offering different strengths based on their medal distributions.

## F Inference Cost

After deploying SLMs, inference is performed orders of magnitude more frequently than fine-tuning, often by many users concurrently. As a result, even small differences in inference efficiency can accumulate into significant computational and energy costs—often exceeding those of fine-tuning. To quantify this, we conducted experiments to measure the computation time and energy consumption required to generate 1,000 tokens during the inference phase. The results, presented in Table A4, were obtained using an NVIDIA L4 GPU, as described in Section 4.1. Among the evaluated models, Phi-1.5B demonstrates the best performance in both computation efficiency and energy consumption.

| No | Model             | Provider     | License     | #Params (B) | Context Length | Training Time      | Size (GB) | Throughput (Tokens/s) | Latency (ms) |
|----|-------------------|--------------|-------------|-------------|----------------|--------------------|-----------|-----------------------|--------------|
| 1  | GPT-Neo-1.3B      | EleutherAI   | Apache 2.0  | 1.37        | 2,048          | 10 days (32 GPUs)  | 2.46      | 1,500                 | 50           |
| 2  | Dolly-v2-3B       | DataBricks   | Apache 2.0  | 3.00        | 2,048          | 10 days (32 GPUs)  | 5.8       | 1,250                 | 55           |
| 3  | Pythia-2.8B       | EleutherAI   | Apache 2.0  | 2.80        | 2,048          | 12 days (32 GPUs)  | 5.5       | 1,350                 | 50           |
| 4  | LLaMA-2-7B        | Meta         | LLAMA 2 L   | 6.47        | 4,096          | 21 days (64 GPUs)  | 13.0      | 1,200                 | 62           |
| 5  | TinyLlama-1.1B    | Hugging Face | Apache 2.0  | 1.10        | 2,048          | 8 days (16 GPUs)   | 2.0       | 1,600                 | 45           |
| 6  | Mistral-7B        | Mistral AI   | Apache 2.0  | 7.00        | 8,192          | 15 days (128 GPUs) | 13.0      | 1,400                 | 55           |
| 7  | Zephyr-7B         | Hugging Face | Apache 2.0  | 7.00        | 8,192          | 20 days (64 GPUs)  | 13.74     | 1,300                 | 52           |
| 8  | ShearedLlama-2.7B | Hugging Face | Apache 2.0  | 2.70        | 2,048          | 12 days (32 GPUs)  | 5.0       | 1,300                 | 54           |
| 9  | Gemma-2B          | Google       | Proprietary | 2.00        | 2,048          | 14 days (32 GPUs)  | 4.67      | 1,450                 | 54           |
| 10 | Phi-1.5B          | Microsoft    | Proprietary | 2.70        | 2,048          | 12 days (32 GPUs)  | 2.45      | 1,400                 | 52           |
| 11 | StableLM-3B       | Stability AI | Apache 2.0  | 3.00        | 2,048          | 14 days (64 GPUs)  | 6.5       | 1,250                 | 50           |
| 12 | Open-LLaMA-3B     | OpenLM       | Apache 2.0  | 3.00        | 4,096          | 18 days (64 GPUs)  | 6.8       | 1,300                 | 60           |
| 13 | Llama-3.2-1B      | Meta         | Llama 3.2   | 1.24        | 128,000        | 30 days (512 GPUs) | 2.47      | 1,350                 | 55           |
| 14 | Phi-3-3.8B        | MIT          | MIT         | 3.82        | 128,000        | 7 days (512 GPUs)  | 2.2       | 1,300                 | 55           |
| 15 | Gemma-3-1B        | Google       | Proprietary | 1.00        | 32,000         | Unknown            | 2         | 1,400                 | 50           |

Table A2: SLMs' Details (sort by release time)

| No | Metric                | Evaluation  | Task   | Datasets                                | Description  |
|----|-----------------------|-------------|--|---|--|
| 1  | <i>Accuracy</i>       | Correctness | Question Answering<br>Classification<br>Recognition<br>Reasoning<br>Problem Solving<br>Reading Comprehension | All<br>except [e2e_nlg, viggo, reuters] | This metric is used for tasks where a model's correctness can be measured by its ability to predict a correct answer, such as in Question Answering (QA) and Classification tasks.           |
| 2  | <i>F1 Score</i>       | Correctness | Question Answering<br>Classification<br>Recognition<br>Reasoning<br>Problem Solving<br>Reading Comprehension | All<br>except [e2e_nlg, viggo, reuters] | A balanced metric that combines precision and recall, ideal for tasks like Named Entity Recognition (NER) and toxicity detection where both false positives and false negatives are crucial. |
| 3  | <i>BLEU</i>           | Correctness | Text Generation<br>Topic Extraction  | e2e_nlg, viggo, reuters                 | Used primarily for evaluating the quality of text generation tasks, such as translation and natural language generation, by comparing generated outputs against reference texts.             |
| 4  | <i>ROUGE</i>          | Correctness | Text Generation<br>Topic Extraction  | e2e_nlg, viggo, reuters                 | Commonly used for summarization tasks, measuring the overlap of n-grams between the generated text and reference summaries.  |
| 5  | <i>METEOR</i>         | Correctness | Text Generation<br>Topic Extraction  | e2e_nlg, viggo, reuters                 | Evaluates generated text quality with consideration for synonyms and paraphrasing based on the harmonic mean of unigram precision and recall, with recall weighted higher than precision.    |
| 6  | <i>Perplexity</i>     | Correctness | Text Generation<br>Topic Extraction  | e2e_nlg, viggo, reuters                 | It is a measurement of uncertainty in the predictions of a language model. In simpler terms, it indicates how surprised a model is by the actual outcomes.                                   |
| 7  | <i>Runtime</i>        | Computation | All  | All                                     | Measures computational efficiency in terms of running time.  |
| 8  | <i>FLOP</i>           | Computation | All  | All                                     | Measures computational efficiency in terms of number of computation per second.  |
| 9  | <i>Cost</i>           | Consumption | All  | All                                     | The total cost of fine-tuning, calculated in USD.  |
| 10 | <i>CO<sub>2</sub></i> | Consumption | All  | All                                     | An estimate of the environmental impact in terms of CO <sub>2</sub> emission of model fine-tuning.   |
| 11 | <i>Energy</i>         | Consumption | All  | All                                     | The total energy consumed during the training process, measured in kilowatt-hours (kWh)  |

Table A3: Metric Details

| Model             | Cost (USD) | Energy (kWh) | CO2 Emissions (kg) | FLOP      | Runtime (h) |
|-------------------|------------|--------------|--------------------|-----------|-------------|
| GPT-Neo-1.3B      | 0.2237     | 0.0186       | 0.011              | 421,420   | 0.1417      |
| Phi-1.5B          | 0.1632     | 0.0136       | 0.008              | 1,780,810 | 0.1033      |
| Open-LLaMA-3B     | 0.3158     | 0.0263       | 0.0155             | 1,850,000 | 0.2         |
| LLaMA-2-7B        | 0.2434     | 0.0203       | 0.0119             | 1,890,000 | 0.154       |
| Mistral-7B        | 0.4211     | 0.0351       | 0.0206             | 5,407,500 | 0.2667      |
| Zephyr-7B         | 0.3158     | 0.0263       | 0.0155             | 3,097,500 | 0.2         |
| TinyLlama-1.1B    | 0.2763     | 0.023        | 0.0135             | 636,170   | 0.175       |
| StableLM-3B       | 0.2368     | 0.0197       | 0.0116             | 855,000   | 0.15        |
| ShearedLlama-2.7B | 0.3684     | 0.0307       | 0.0181             | 1,955,250 | 0.2333      |
| Dolly-v2-3B       | 0.2171     | 0.0181       | 0.0106             | 740,000   | 0.1375      |
| Pythia-2.8B       | 0.2632     | 0.0219       | 0.0129             | 833,000   | 0.1667      |
| Gemma-2B          | 0.3421     | 0.0285       | 0.0168             | 1,435,000 | 0.2167      |
| Llama-3.2-1B      | 0.4342     | 0.0362       | 0.0213             | 7,083,330 | 0.275       |
| Phi-3-3.8B        | 0.4079     | 0.034        | 0.02               | 6,000,000 | 0.2583      |
| Gemma-3-1B        | 0.4474     | 0.0373       | 0.0219             | 5,666,670 | 0.2833      |

Table A4: SLMs' Inference Cost