OckBench: Measuring the Efficiency of LLM Reasoning

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Abstract

Large language models (LLMs) such as GPT-5 and Gemini 3 have pushed the frontier of automated reasoning and code generation. Yet current benchmarks emphasize accuracy and output quality, neglecting a critical dimension: efficiency of token usage. The token efficiency is highly variable in practical. Models solving the same problem with similar accuracy can exhibit up to a **5.0**× difference in token length, leading to massive gap of model reasoning ability. Such variance exposes significant redundancy, highlighting the critical need for a standardized benchmark to quantify the gap of token efficiency. Thus, we introduce OckBench, the first benchmark that jointly measures accuracy and token efficiency across reasoning and coding tasks. Our evaluation reveals that token efficiency remains largely unoptimized across current models, significantly inflating serving costs and latency. These findings provide a concrete roadmap for the community to optimize the latent reasoning ability, token efficiency. Ultimately, we argue for an evaluation paradigm shift: tokens must not be multiplied beyond necessity. Our benchmarks are available at https://ockbench.github.io/.

1 Introduction

"Entities must not be multiplied beyond necessity."

— The Principle of Ockham's Razor

Large Language Models (LLMs) like GPT-5, Gemini 3, and Claude serve as the frontier of automated intelligence, fueled by reasoning techniques like Chain of Thought (CoT) [37]. As the field embraces test-time compute scaling [34], models are increasingly trained to generate extensive token chains to tackle tougher problems. However, this massive inflation of decoding tokens introduces a critical bottleneck. Solving just six problems in the International Olympiad in Informatics can now take over ten hours [26], and complex mathematical challenges (e.g., Putnam math [24]) frequently explode into millions of tokens, turning inference into continuous decoding marathons [23].

While the community celebrates these gains in reasoning capability, prevailing benchmarks like HELM [19] and Chatbot Arena [5] focus almost exclusively on *output quality*, largely ignoring this token efficiency crisis. We argue that this one-dimensional evaluation fails to provide a holistic view of true model intelligence. In reality, many models consume vastly more tokens than necessary to reach the correct answer. As shown in Figure 2a, models of identical size (7B) achieving similar accuracy can differ by over **3.3**× in token consumption and **5.0**× in end-to-end latency.

As models continue to scale and accuracy on standard tasks approaches saturation, relying solely on correctness is no longer sufficient to distinguish capability. This massive variance in computational cost for the exact same correct answer exposes a fundamental blind spot. We propose that efficiency is not merely a logistical constraint, but a proxy for intelligence itself. To comprehensively evaluate a model's true capability and address the pressing bottlenecks in real-world serving, we introduce OckBench: the first benchmark

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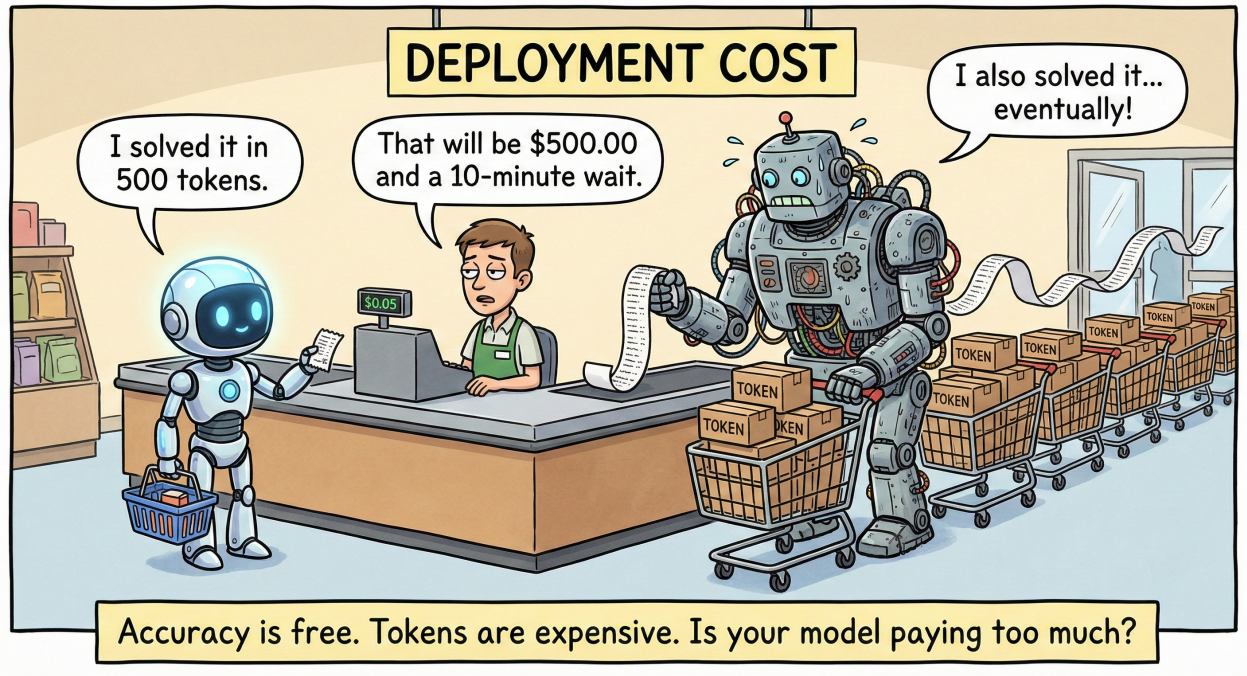


Figure 1: **The Overthinking Tax.** Both agents achieve the same accuracy, yet the verbose model incurs higher latency and cost.

that jointly measures accuracy and token consumption to evaluate deployment-ready reasoning. Through this framework, we formalize the concept of *Per-Token Intelligence*—a critical, yet previously unmeasured dimension that defines a model's ability to solve complex problems not just correctly, but concisely.

To quantify this new dimension of intelligence, we construct OckBench across three core domains: math, coding, and science, drawing from datasets that strictly require reasoning capability, such as AIME, MBPP and GPQA. Rather than evaluating models on randomly sampled questions, OckBench deliberately selects problems of moderate difficulty that naturally elicit a wide variance in token consumption. By focusing on these specific instances, we clearly expose the intrinsic efficiency gap between models that can solve problems concisely and those that resort to verbose babbling. Finally, to provide a holistic ranking, we design the OckScore (S_{Ock}), a unified evaluation metric that logarithmically penalizes unnecessary verbosity while fundamentally prioritizing correctness.

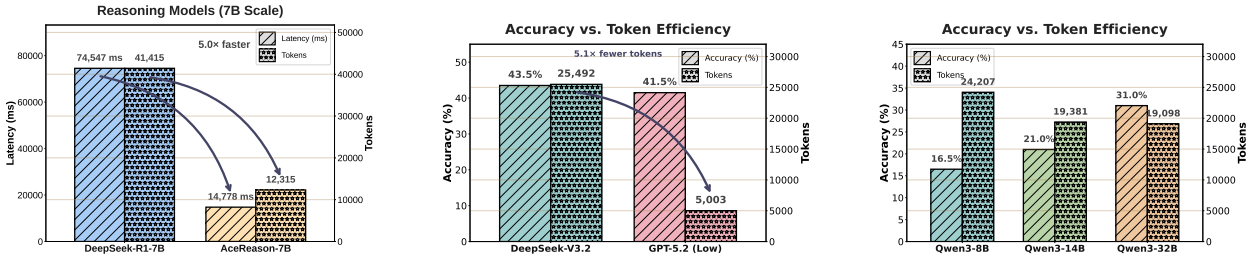
Through extensive evaluations on OckBench, we uncover several critical insights into the current landscape of LLM reasoning. First, we observe an efficiency gap between open-weights and proprietary models. While top-tier open models have nearly closed the performance gap in pure accuracy, they heavily rely on brute-force verbosity. For instance, as shown in Figure 2b, an open-weights model might consume over $\mathbf{5}\times$ the tokens of a closed-source counterpart to solve the exact same problem and achieve comparable accuracy.

Second, we identify a counterintuitive phenomenon within model families: the "Overthinking Tax". While smaller models are generally assumed to be more economical, Figure 2c reveals they often compensate for lower parameter capacity by generating excessively long reasoning chains. Because they consume significantly more tokens to reach the same answer, these ostensibly "cheaper" models paradoxically incur higher latency and total operational costs than their larger counterparts in real-world deployment.

Finally, analyzing the trajectory of frontier models in Figure 3, we observe that newer generations simultaneously improve in both accuracy and token efficiency. This validates our core premise: correctness and efficiency are not isolated metrics, but joint indicators of true intelligence. To meaningfully advance automated reasoning, the community must evaluate and co-optimize both dimensions.

To bridge the gap between pure reasoning accuracy and holistic model intelligence, our core contributions are summarized as follows:

- **The Concept of Per-Token Intelligence:** We introduce a new dimension for evaluating LLMs, proposing that a superior model must not only achieve high accuracy but do so with minimal token



(a) Reasoning Efficiency in 7B Models

(b) Open vs. Closed Source Token Efficiency

(c) The Overthinking Tax in Model Families

Figure 2: **The Efficiency Gap and Overthinking Tax in Reasoning Models.** (a) Despite having the same parameter scale (7B), models can exhibit a 5× difference in latency due to disparate token consumption, emphasizing token efficiency as a critical system bottleneck. (b) While open-weights models (DeepSeek-V3.2) now rival proprietary models (GPT-5.2) in accuracy, they suffer a massive efficiency gap (e.g., consuming 5.1× more tokens), underscoring the necessity of optimizing *Per-Token Intelligence*. (c) Across the Qwen3 series, larger models achieve higher accuracy while consuming *fewer* tokens. Smaller models pay a high "Overthinking Tax" by generating verbose, inefficient reasoning, making them paradoxically more expensive in real-world deployment.

consumption. This paradigm shift provides a concrete roadmap for the community to optimize reasoning capability.

- **OckBench Framework and OckScore:** We present the first hardware-agnostic benchmark that jointly measures accuracy and token efficiency. By employing a novel "Differentiation Filter," OckBench isolates tasks that expose the intrinsic efficiency gap between models. Furthermore, we design the OckScore (S_{Ock}), a unified metric that quantitatively penalizes unnecessary verbosity.
- **Empirical Insights and the "Overthinking Tax":** We systematically evaluate a diverse roster of models, quantifying a severe efficiency gap between open-weights and proprietary architectures. Furthermore, we formally define the "Overthinking Tax," proving that smaller models often incur paradoxically higher deployment costs due to inefficient, verbose reasoning.
- **Validating Optimization Pathways:** We demonstrate that reasoning efficiency is a tractable dimension for optimization. Through training-free model interpolation and difficulty-aware reinforcement learning, we show that models can successfully "Ockhamize" their reasoning and significantly improve their OckScore.

2 Background & Related Work

2.1 The Blind Spot in Current Evaluations

Current benchmarks typically focus on either output quality or system performance, leaving a critical gap.

Accuracy-Centric Benchmarks. Suites like HELM [19] and LM-Eval [12] prioritize correctness. While useful for gauging capability, they treat generation as a black box, ignoring computational costs. Furthermore, preference-based metrics often favor verbose responses, incentivizing models to inflate token counts without adding value – a phenomenon known as *length bias*.

System-Centric Benchmarks. Benchmarks like MLPerf [31] focus on throughput and latency. These measure the *engine* (infrastructure) but not the *driver* (reasoning process). An optimized engine cannot compensate for a model that generates 5× more tokens than necessary.

2.2 The Rising Cost of Reasoning

The need for token-aware evaluation grows with the rise of inference-time compute scaling. As models shift to multi-step reasoning, output lengths explode. Epoch AI reports that reasoning model outputs grow

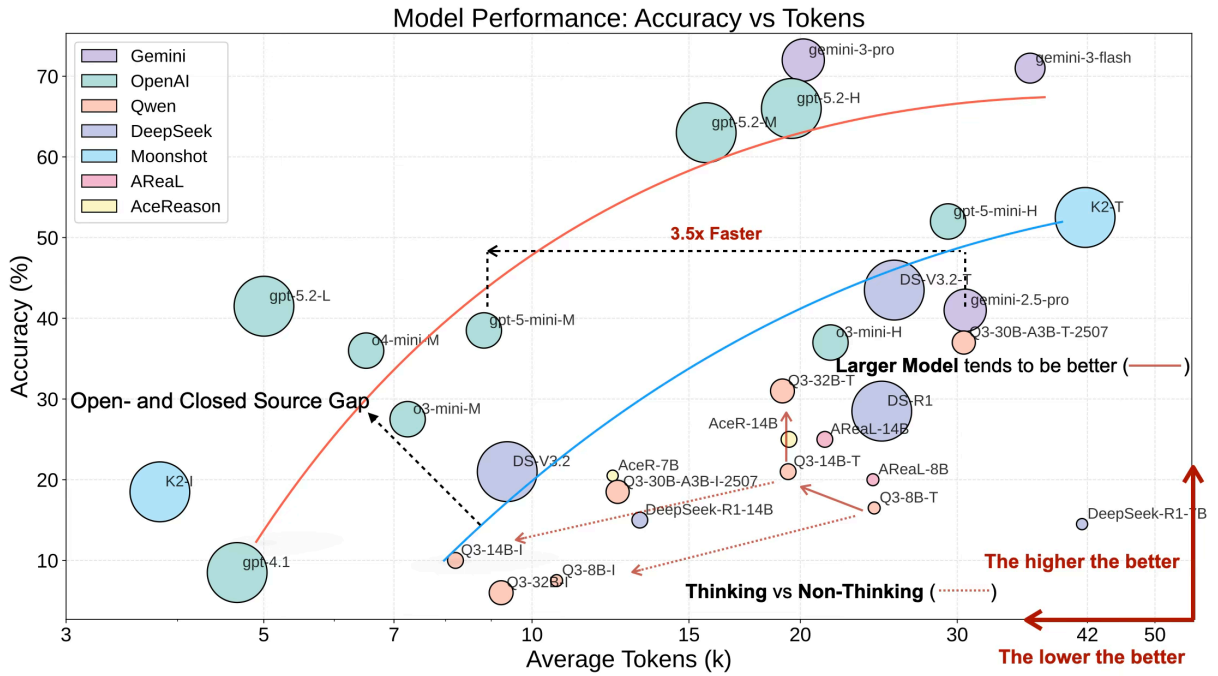


Figure 3: **Accuracy vs. Token Consumption.** A bubble plot illustrating the trade-off between reasoning accuracy (y-axis) and computational cost (x-axis, log scale) across top-tier models. Bubble size indicates model parameter count. The distribution highlights the lack of correlation between pure accuracy and efficiency.

approximately 5× annually, compared to 2.2× for standard models [10].

This trend has practical consequences. Since inference cost scales linearly with token count, providers billing by the token [33] inadvertently penalize efficient reasoning. Without metrics to curb "token bloat," the industry risks optimizing for models that are knowledgeable but operationally intractable.

2.3 Optimization and The "Overthinking" Problem

Existing efficiency research focuses largely on compression (quantization) or system optimizations (FlashAttention) [7, 18, 21], which treat the output distribution as fixed.

Our work targets an orthogonal optimization: **Algorithmic Efficiency.** Recent studies show models often "overthink," generating circular reasoning without improving accuracy [10]. OckBench quantifies this inefficiency, aiding methods like Difficulty-Aware Training (DIET [3]) or model interpolation [38] that aim to boost the *intelligence-per-token* ratio.

3 Benchmark Design: OckBench

OckBench is designed to decouple *reasoning efficiency* from *reasoning capability*. Unlike traditional benchmarks that solely rank models by accuracy, OckBench introduces a selection mechanism that isolates tasks where models exhibit significant divergence in computational cost. This section details our domain composition, our efficiency-sensitive item selection strategy, and our standardized evaluation protocol.

3.1 Benchmark Composition

To ensure broad coverage of reasoning modalities, OckBench aggregates tasks across three complementary domains: mathematics, software engineering, and scientific reasoning.

Mathematics and Reasoning. Mathematical problem-solving serves as the core testbed for logical rigor. We construct our pool from established benchmarks including GSM8K [6], AIME 2024/2025, Olympiad-Bench [15], MATH500 [20], math subset of Humanity's Last Exam [30]and AMO-Bench [1]. To probe frontier reasoning capabilities beyond current saturation points, we additionally incorporate the mathematics subset of Humanity's Last Exam. These datasets cover a spectrum of difficulty from grade-school arithmetic to competition-level number theory.

Software Engineering. Code generation proxies real-world logical synthesis and planning. We utilize a lightweight variant of MBPP [2] and LiveCodeBench [17] to assess practical programming skills.

Scientific Reasoning. We include ScienceQA [22], the STEM subsets of MMLU [16], and GPQA-Diamond [32] to test knowledge-constrained reasoning and concision under technical load.

3.2 Item Selection Strategy: The Differentiation Filter

A naive random sampling of problems is insufficient for benchmarking efficiency. If a problem is too simple, all models solve it concisely (floor effect); if too complex, all models generate long, often incorrect chains (ceiling effect). To ensure OckBench is *sensitive* to intrinsic differences in model efficiency, we employ a *Differentiation Filter*.

Formally, let $\mathcal{M}$ be a diverse set of representative models and $\mathcal{D}_{pool}$ be the initial dataset pool. For each problem $x \in \mathcal{D}_{pool}$, we collect the set of generated token lengths $\mathcal{L}_x = \{\text{len}(m(x)) \mid m \in \mathcal{M}\}$. We select the final benchmark set $\mathcal{D}_{ock}$ based on two criteria:

1. **Difficulty Banding:** We filter for problems where the average accuracy across $\mathcal{M}$ falls within a target band of $0.1 \leq \text{acc}(x) \leq 0.9$. This removes trivial instances and intractable queries, focusing on the "reasoning frontier" where efficiency matters most.

2. **Maximizing Token Variance:** From the remaining pool, we select the top-k instances that maximize the variance of token consumption, $\text{Var}(\mathcal{L}_x)$.

Rationale. High variance in token consumption implies that a problem admits multiple valid reasoning paths—some efficient, some convoluted. By selecting these instances, OckBench highlights the *Efficiency Gap*: the difference between a model that "Ockhamizes" its reasoning and one that "babbles". This ensures that the benchmark penalizes unnecessary verbosity rather than penalizing the necessary complexity required for hard problems.

3.3 Evaluation Protocol

To guarantee reproducibility and fair comparison, we adhere to a strict evaluation protocol.

Inference Settings. We use single-shot prompts and greedy decoding (temperature = 0) to reduce prompt effects and sampling noise.

Correctness Metrics. Accuracy is measured via Pass@1. For mathematics and science tasks, we employ rule-based answer extraction and exact matching against the ground truth. For coding tasks, correctness is verified via functional execution against a suite of unit tests.

Efficiency Metric (Output Tokens). We define "Output Tokens" as the raw count of tokens generated by the model's specific tokenizer prior to the end-of-sequence (EOS) token. Output Tokens include both intermediate reasoning and final answer tokens. While tokenizers differ between architectures, this metric accurately reflects the true deployment cost (latency and compute) specific to each model.

3.4 Unified Score

To design a unified score that can assess both a model's performance on accuracy and efficiency, we propose the *OckScore* (S_{ock}). Current benchmarks typically treat accuracy and computational cost as orthogonal metrics; however, in deployment scenarios, they are inextricably linked. A model that achieves the correct

answer through concise reasoning is strictly superior to one that arrives at the same conclusion through excessive "token babbling," and both are superior to a model that is confident (verbose) but wrong.

Formally, we define our design philosophy through the following preference ordering:

$$\langle \textsc{Correct}, \textsc{Short} \rangle \succ \langle \textsc{Correct}, \textsc{Long} \rangle \succ \langle \textsc{Wrong}, \textsc{Short} \rangle \succ \langle \textsc{Wrong}, \textsc{Long} \rangle$$

To capture this ordinal relationship quantitatively, we introduce a penalized accuracy metric defined as:

$$S_{\text{ock}} = \text{Accuracy} - \lambda \cdot \log\left(\frac{T}{C}\right)$$

where Accuracy is the percentage pass rate (0-100), T is the average number of output tokens, λ is a penalty coefficient, and C is a normalization constant. In our experiments, we set $\lambda = 10$ and $C = 10,000$.

The design of this metric is justified by three key considerations:

Accuracy Prioritization. We fundamentally posit that correctness is the primary utility of a reasoning model. By using accuracy as the base term (0-100) and subtracting a logarithmic penalty, we ensure that efficiency is treated as a *cost* rather than a multiplier. This structure guarantees that a correct solution, no matter how verbose, generally outscores an incorrect one, preserving the boundary between useful and useless models.

Logarithmic Scaling of Efficiency. We employ a logarithmic penalty ($\log T$) rather than a linear one. Reasoning chains vary by orders of magnitude (e.g., 1k vs. 100k tokens). A linear penalty would either be negligible for short chains or disproportionately punitive for long, necessary reasoning. The logarithmic scale compresses this variance, acknowledging that the marginal cost of tokens diminishes in distinctiveness at higher scales, while preventing floor effects where slight verbosity differences in small models dominate the score.

Calibration with Model Priors. The parameters $\lambda = 10$ and $C = 10,000$ were calibrated to align the score with strong empirical priors regarding "per-token intelligence." We operate under the hypothesis that models with higher intelligence (historically, larger commercial models) should optimize the trade-off between accuracy and brevity better than weaker models. Empirically, this parameterization ensures that the score does not falsely promote "short but dumb" models. It yields a ranking where capable commercial models and larger parameter models within the same family (e.g., 32B vs. 8B) score highest, reflecting their ability to condense complex reasoning into efficient paths, whereas smaller or weaker models are penalized for the "overthinking" tax described in Section 5.

4 Experiments

4.1 Experimental Setup and Protocol

Benchmark Composition. To ensure a holistic evaluation of reasoning efficiency, OckBench aggregates tasks across three complementary domains: Mathematics, Software Engineering, and Scientific Reasoning.

- **Mathematics:** We construct our pool from established benchmarks including GSM8K and competition-level datasets such as AIME 2024/2025 and AMO-Bench.
- **Software Engineering:** We utilize variant problems from MBPP and LiveCodeBench to assess practical programming capabilities.
- **Scientific Reasoning:** We incorporate subsets from ScienceQA, MMLU (STEM subjects), and GPQA-Diamond to test reasoning constrained by domain-specific knowledge.

Note: While OckBench covers these three domains, the results and analysis in this section and Section 5 focus primarily on the **Mathematics** subset (OckBench-Math)

Item Selection Strategy. To decouple reasoning efficiency from capability, we employ the *Differentiation Filter* (see Section 3.2). Rather than randomly sampling, we select the top 200 instances exhibiting the greatest variance in token consumption across models. These instances represent the "reasoning frontier" where models diverge most significantly—some solving them concisely, others engaging in excessive "token babbling." This ensures that token count serves as a high-contrast signal for efficiency.

Table 1: **OckBench-Math Leaderboard.** Models are ranked by OckScore (S_{ock}). Gemini 3 Pro achieves the highest efficiency score, balancing high accuracy with moderate token consumption.

Model	Org	#Tokens	Accuracy (%)	Reasoning Efficiency
gemini-3-pro-preview	Gemini	20,154	72.0	67.21
gemini-3-flash-preview	Gemini	36,212	71.0	64.35
gpt-5.2_high	OpenAI	19,541	66.0	61.30
gpt-5.2_medium	OpenAI	15,683	63.0	58.90
gpt-5-mini_high	OpenAI	29,297	52.0	46.06
Kimi-K2-Thinking	Kimi	41,746	52.5	45.36
gpt-5.2_low	OpenAI	5,003	41.5	39.74
DeepSeek-V3.2-Thinking	DeepSeek	25,492	43.5	38.00
o4-mini_high	OpenAI	25,677	43.5	37.98
gemini-2.5-pro	Gemini	30,622	41.0	34.91
Qwen3-235B-A22B-Thinking-2507	Qwen	28,558	38.5	32.64
o3-mini_high	OpenAI	21,623	37.0	32.00
Qwen3-235B-A22B-Instruct-2507	Qwen	7,707	27.0	24.52
DeepSeek-R1	DeepSeek	24,685	28.5	23.10
AReaL-boba-2-32B	AReaL	23,327	27.0	21.77
AceReason-Nemotron-14B	AceReason	19,424	25.0	20.31
DeepSeek-R1-Distill-Qwen-32B	DeepSeek	12,895	15.5	11.90

Evaluation Protocol. All models are evaluated in a single-shot setting to minimize prompt-engineering biases. We employ an LLM-based extraction method where an auxiliary model parses the final answer (e.g., a mathematical value or code block) from the raw response. Correctness is measured via *Pass@1* accuracy. Efficiency is quantified by *Average Output Tokens*, counting the raw tokens generated prior to the end-of-sequence (EOS) token.

4.2 Models

We evaluate a diverse roster of state-of-the-art models, covering both proprietary and open weights across various scales of reasoning effort:

- **Commercial Models:** We evaluate Google's **Gemini 3** [14] and **Gemini 2.5** [8] families. From OpenAI, we evaluate the **GPT-5.2** [28] and **GPT-5-mini** [27] series across three distinct reasoning effort levels (High, Medium, Low), alongside **o3-mini**, **o4-mini** [29], and standard instruction-tuned models like GPT-4o [25].
- **Open-Source Models:** We evaluate a comprehensive suite of open-weights models, led by the **Qwen3** family [36] (including "Thinking" and "Instruct" variants from 4B up to 235B parameters). We also include the **DeepSeek** series, covering the V3.2 and R1 architectures [9, 13], and the **Kimi-K2** series [35]. This is further complemented by the **AReaL-boba-2** series [11] and the **AceReason-Nemotron** models [4].

4.3 Main Results

Table 1 presents the comprehensive results on OckBench-Math, ranking models by our proposed OckScore (S_{Ock}). Figure 3 illustrates the trade-off between accuracy and token consumption. We observe several critical trends:

The Efficiency Gap in Frontier Models. Commercial models dominate the leaderboard yet exhibit stark differences in efficiency. **Gemini-3-Pro** achieves the highest performance with 72.0% accuracy while consuming an average of 20,154 tokens ($S_{Ock} = 67.21$). In contrast, **Gemini-3-Flash** achieves comparable accuracy (71.0%) but requires nearly double the computation (36,212 tokens), resulting in a lower score (64.35). This highlights that distinct models within the same family can possess vastly different "per-token intelligence"—the Flash model effectively compensates for lower parameter capacity by generating significantly longer chains of thought.

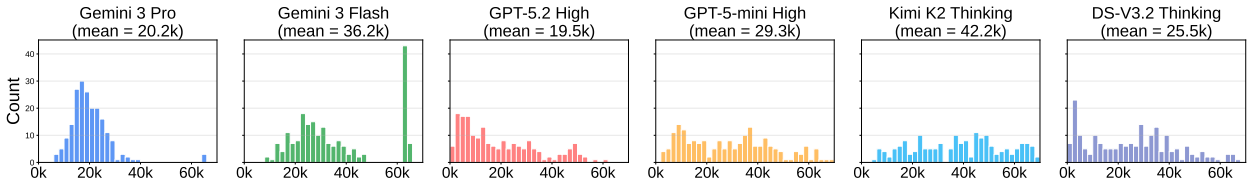


Figure 4: **Token Distribution Across Problems.** Histogram of output-token counts on OckBench-Math for six frontier models (Gemini 3 Pro/Flash, GPT-5.2/5-mini, DeepSeek-V3.2-Thinking and Kimi-K2-Thinking). The distributions expose large variance in reasoning verbosity and reveal saturation behavior for some models near their generation limits.

Kimi-K2 and the Open-Source Trade-off. Among open-weights models, **Kimi-K2-Thinking** emerges as the strongest performer, achieving 52.5% accuracy. Notably, it not only outperforms commercial baselines like GPT-5.2 Low (41.5%) but also rivals **GPT-5-mini High** (52.0%). However, this accuracy comes at a steep computational price: Kimi-K2 consumes an average of 41,746 tokens—the highest in our evaluation and nearly 43% more than GPT-5-mini High (29,297 tokens). This reveals a significant "Efficiency Gap": while top-tier open models have successfully closed the distance in reasoning *accuracy*, they still rely on brute-force, verbose reasoning strategies compared to the more concise paths of commercial models.

Summary. These results validate that accuracy alone is an insufficient metric. Top-performing models distinguish themselves not just by correctness, but by achieving it without the excessive verbosity that plagues less capable or poorly optimized models. While open-source models like Kimi-K2 are reaching commercial-grade accuracy, their lower S_{Ock} scores highlight the urgent need for optimization in reasoning density.

5 Analysis

This section analyzes the token consumption and efficiency of models using OckBench-Math.

5.1 Token Distribution Analysis

Figure 4 summarizes token usage across problems as a distribution, making variance and tail behavior immediately visible. Figure 4 illustrates the distribution of token usage, highlighting variance and tail behaviors. Two patterns emerge: first, output spread varies significantly, with some models exhibiting long, verbose tails. Second, a "saturation" mass appears at the right tail, indicating models frequently hit generation limits where reasoning collapses or loops.

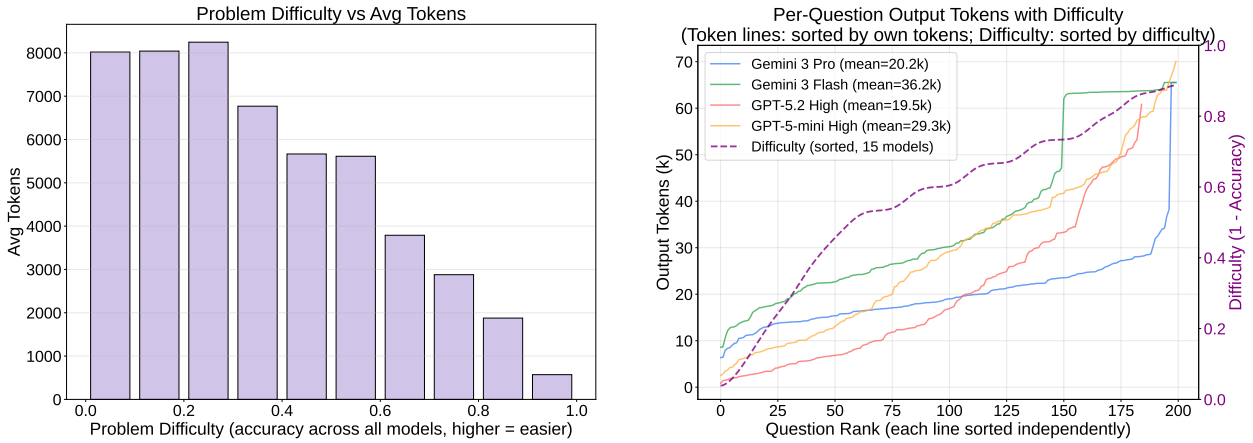
Figure 5b dissects this by problem difficulty, revealing two distinct strategies:

Adaptive vs. Uniform Scaling. The GPT series (GPT-5.2 and GPT-5-mini) exhibits a clear *difficulty-adaptive* trend. As problem difficulty increases (dashed purple line), token consumption rises in a gradual linear or super-linear fashion, suggesting that these models allocate budget proportional to perceived complexity. In contrast, the Gemini family (e.g., Gemini 3 Pro) shows a comparatively *flat* profile over most of the benchmark (ranks 0 to 190), with token output remaining stable (˜20k) and largely insensitive to incremental difficulty.

The "Reasoning Cliff" and Per-Token Intelligence. A critical observation is the "saturation wall" or "cliff" in the Gemini models. Unlike the gradual ramp of the GPT series, Gemini models exhibit a sharp vertical asymptote where token usage spikes abruptly to the model's generation limit (likely the context window cap). In the histogram (Figure 4), this manifests as a distinct frequency spike at the maximum token range (∼64k) for Gemini 3 Flash.

Comparing Gemini 3 Flash and Gemini 3 Pro reveals that this "cliff" is a proxy for model capacity. Gemini 3 Flash hits this saturation point much earlier (around rank 150 in Figure 5b) compared to Pro (rank 195). We argue that the delay of this cliff is a direct indicator of *per-token intelligence*: Gemini 3 Pro

resolves complex reasoning paths more succinctly than Flash, deferring the onset of "reasoning collapse". This validates our hypothesis that efficiency is not only about speed, but about the information density of the generated reasoning chain.



(a) **Reasoning Cost vs. Difficulty.** Analysis across 9 OpenAI models and 3,579 math problems. Average token consumption generally correlates with difficulty but exhibits a resource-intensive "overthinking" tail on the most intractable problems (where accuracy is near zero).

(b) **Token Consumption Profiles.** Comparison of four representative models (Gemini 3 Pro/Flash and GPT-5.2/5-mini). Problems are sorted by output token count for each model. The dashed purple line indicates smoothed problem difficulty, revealing distinct scaling behaviors between model families.

Figure 5: Analysis of reasoning costs and token consumption scaling across different models.

5.2 Tokens vs Difficulty

To quantify how reasoning effort scales with problem complexity, we analyze the relationship between token consumption and problem difficulty, defined here as the average accuracy across all 37 evaluated models. Figure 5a presents the average output tokens for 9 OpenAI reasoning models. We observe a strong negative correlation: as expected, harder problems (lower accuracy) generally necessitate longer reasoning chains. However, a critical inefficiency emerges at the lower bound of accuracy. For intractable problems where models fail to find the correct answer (Accuracy ≈ 0), token consumption does not plateau but rather maintains a high variance. This indicates an "overthinking" behavior, where models expend vast computational resources generating extensive reasoning traces that ultimately fail to converge, effectively paying a high latency cost for zero utility.

5.3 The "Overthinking Tax": When Efficient Models Pay More

One of OckBench's most critical insights is the identification of an *Overthinking Tax*—a phenomenon where models optimized for deployment efficiency (via smaller parameter counts or lower unit pricing) paradoxically incur higher total costs due to excessive verbosity.

Common intuition posits that "smaller is cheaper". To verify this, we conducted a cost analysis using real-world API pricing from SiliconFlow[1]. Comparing DeepSeek-R1-Distill-Qwen-7B and 14B reveals a stark financial inversion. While the 7B model is priced at **50%** of the 14B model per token, it generates 3.13× more output tokens ($41,415$ vs $13,211$) to achieve worse accuracy.

When translating to cost-per-query, the "cheaper" 7B model is effectively **57% more expensive** than the 14B model (14.5 unit cost vs 9.2 unit cost). This demonstrates that aggressive pricing on smaller models is completely negated by the *Overthinking Tax*, rendering them economically inefficient despite their low parameter count. This case demonstrates that efficiency cannot be defined solely by *cost-per-token* or *parameters*. Without the token-aware evaluation provided by OckBench, developers may unknowingly deploy "efficient" models that act as "verbose" bottlenecks, inflating total request latency and operational costs.

[1]Pricing data as of Jan 2026: DeepSeek-R1-Distill-Qwen-7B at \$0.05/1M tokens vs. 14B at \$0.1/1M tokens.

5.4 Efficiency Gap and Trends

Our analysis of the OckBench-Math leaderboard (Figure 3) reveals two critical trends defining the current landscape of reasoning models.

1. The Open-Closed Efficiency Gap. A distinct dichotomy exists between proprietary and open-weights models. While open-source models are closing the accuracy gap, they remain clustered in the lower-right quadrant of the plot—characterized by high token consumption for moderate accuracy. The gap is no longer just about capability, but significantly about *efficiency*. Bridging this divide requires the open-source community to pivot from pure parameter scaling to optimizing reasoning density.

2. Rapid Convergence of Frontier Models. The trajectory of frontier models validates *Per-Token Intelligence* as the primary optimization objective. As illustrated in Figure 3, comparing **gpt-5-mini-medium** with **gemini-2.5-pro** reveals a massive efficiency gap: despite achieving comparable accuracy ($\approx 40\%$), the latter consumed $3.5\times$ more tokens. However, the subsequent generation **gemini-3** has rapidly closed this gap with **gpt-5.2**, shifting towards the Pareto frontier. This swift iteration demonstrates that frontier laboratories are actively optimizing for reasoning efficiency, offering a clear roadmap for open-source development.

6 Improvement Methods

We demonstrate how OckBench verifies efficiency-oriented optimization using two approaches: training-free model interpolation and difficulty-aware reinforcement learning (RL).

6.1 Training-Free Optimization: Model Interpolation

We merge the reasoning of "Thinking" models with the conciseness of "Instruct" models via weight interpolation [38], targeting `Qwen3-Instruct` and `Qwen3-Thinking` checkpoints. Using $\theta_{merged} = 0.6 \cdot \theta_{thinking} + 0.4 \cdot \theta_{instruct}$, we aim to retain reasoning depth while imposing brevity.

Results. The interpolated model (`Qwen3-Mix-6:4`) substantially improves efficiency:

Token Reduction: Average length drops to **12,092 tokens** (from ∼27k).

Accuracy: Relies at **20.0%**, slightly below pure Thinking but above Instruct.

OckScore: Increases to **17.06**.

Interpolation effectively prunes redundant reasoning without retraining.

6.2 Training-Based Optimization: Difficulty-Aware RL

We also employ DIET (Difficulty-Aware Training) [3], an RL framework with dynamic token penalties to mitigate overthinking. We fine-tune `DeepSeek-R1-Distill-Qwen-7B` on DeepScaleR, penalizing length on simple queries while preserving it for complex ones.

Results. Post-training evaluation shows:

Accuracy: Improves to **15.5%** (baseline 14.5%).

Token Efficiency: Average tokens decrease to **23,671** (from 41,415).

OckScore: Jumps to **10.23** (from 7.39).

Table 2 summarizes these results, confirming that reasoning efficiency is a tractable dimension for optimization.

7 Conclusion

In this work, we introduced OckBench, the first model- and hardware-agnostic benchmark designed to measure *Per-Token Intelligence*—the critical trade-off between reasoning accuracy and token consumption. By employing a *Differentiation Filter*, we moved beyond standard accuracy metrics to isolate problems that expose the "Efficiency Gap" between models. We proposed the OckScore (S_{Ock}), a unified metric that penalizes unnecessary verbosity, establishing a new standard for evaluating deployment-ready reasoning.

Our extensive experiments on frontier and open-source models reveal that token efficiency is a significant, yet previously neglected, axis of differentiation. We identified the *Overthinking Tax*, where smaller, distilled models often expend exorbitant computational resources to mimic complex reasoning patterns without

Table 2: **Effectiveness of Efficiency Optimizations.** Comparison of model interpolation (Qwen3-Mix) and difficulty-aware RL (DeepSeek-DIET) against logical baselines on OckBench-Math, showing improvements in OckScore.

Model Strategy	Acc (%)	Avg Tokens	OckScore
Interpolation Method			
Qwen3-4B-Thinking	22.0	27,238	16.29
Qwen3-4B-Instruct	13.5	11,859	10.10
Qwen3-Mix-6:4 (Ours)	**20.0**	**12,092**	**17.06**
RL Optimization Method			
DeepSeek-Distill-Qwen-7B	14.5	41,415	7.39
DeepSeek-DIET (Ours)	**15.5**	**23,671**	**10.23**

converging to correct answers, sometimes incurring higher per-query costs than their larger counterparts despite lower per-token pricing. Furthermore, we demonstrated that efficiency is not a fixed property of model scale but a tractable dimension for optimization. Through model interpolation and Difficulty-Aware Training, we showed that models can be aligned to "Ockhamize" their reasoning, significantly improving their OckScore without retraining from scratch.

We argue that the community must shift from an accuracy-centric evaluation paradigm to one that treats tokens as a cost rather than a free resource. OckBench provides the necessary platform to guide this transition, fostering the development of models that are not only intelligent but also operationally viable. Future work may extend this framework to explore dynamic compute allocation, token-pruning strategies, and efficiency in multimodal reasoning contexts.

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