# How Efficient is LLM-Generated Code? A Rigorous & High-Standard Benchmark

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https://github.com/q-rz/enamel

ICLR

## PROPOSED BENCHMARK: ENAMEL

**HumanEval Canonical: $2^{\Theta(n)}$ recursions**

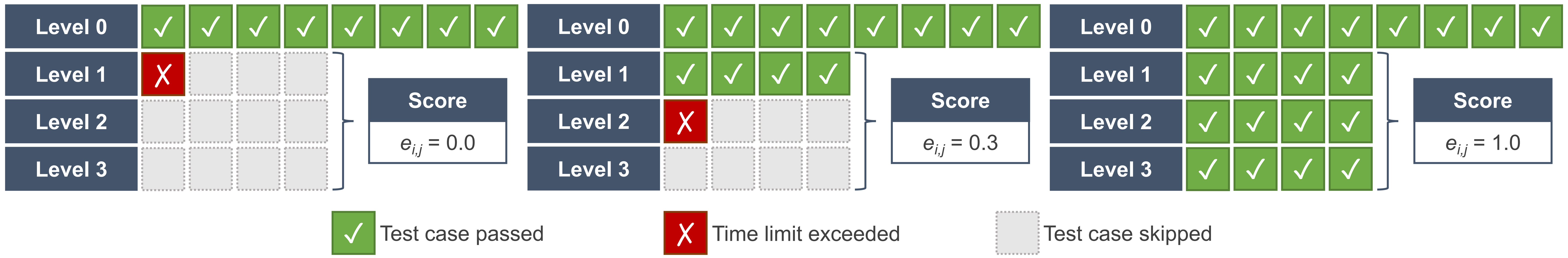
```python
def fib(n):
  if n == 0:
    return 0
  if n == 1:
    return 1
  return fib(n - 1) + fib(n - 2)
```

**GPT-4 Turbo: $\Theta(n)$ iterations**

```python
def fib(n):
  a, b = 0, 1
  for _ in range(n):
    a, b = b, a + b
  return a
```

**Our Expert: $\Theta(\log n)$ iterations**

```python
def fib(n):
  if n == 0: return 0
  a, b = 0, 1
  for n in bin(n)[3 :]:
    a, b = a * a + b * b, b * (a * 2 + b)
    if n == '1': a, b = b, a + b
  return b
```




**Example (*n*-th Fibonacci):** · **Level 0:** $n \le 10$ · **Level 1:** $n \le 30$ · **Level 3:** $n \le 9\,000$ · **Level 3:** $n \le 10\,000$

## PROPOSED METRIC: eff@*k*

- Proposed **metric** $\mathrm{eff}_i@k$ (a generalization of $\mathrm{pass}_i@k$):

$$\mathrm{eff}_i@k := \mathbb{E}_{c_{i,1},\dots,c_{i,k}}[\max_{j=1}^{k} e_{i,j}];$$

  - $c_{i,j}$: the $j$-th LLM-generated code sample for problem $i$;
  - $e_{i,j}$: the efficiency score of code $c_{i,j}$ compared with our human expert.
- An **estimator** $\widehat{\mathrm{eff}}_i@k$ for $\mathrm{eff}_i@k$ using $n \ge k$ code samples:
  - Let $e_{i,(r)}$ be the $r$-th smallest score among $e_{i,1},\dots,e_{i,n}$. **Estimator**:

$$\widehat{\mathrm{eff}}_i@k := \sum_{r=k}^{n}\binom{r-1}{k-1}e_{i,(r)} \Big/ \binom{n}{k}.$$

  ✓ **Unbiasedness**: for any $n \ge k$,

$$\mathbb{E}_{c_{i,1},\dots,c_{i,n}}\Big[\sum_{r=k}^{n}\binom{r-1}{k-1}e_{i,(r)} \Big/ \binom{n}{k}\Big] = \mathbb{E}_{c_{i,1},\dots,c_{i,k}}[\max_{j=1}^{k} e_{i,j}].$$

  ✓ **Variance reduction**: for any $n \ge k$,

$$\mathrm{Var}_{c_{i,1},\dots,c_{i,n}}\Big[\sum_{r=k}^{n}\binom{r-1}{k-1}e_{i,(r)} \Big/ \binom{n}{k}\Big] \le \frac{k}{n}\mathrm{Var}_{c_{i,1},\dots,c_{i,k}}[\max_{j=1}^{k} e_{i,j}].$$

  - A **numerically stable** implementation: See our paper for detail…

## EXPERT-WRITTEN SOLUTIONS

- **Problemset**: 142 problems selected from HumanEval.
- **Our expert solutions**: much more **efficient** than HumanEval+'s.

| ID | Problem Description | HumanEval+ Solution | Our Expert Solution |
|---|---|---|---|
| #10 | Find the shortest palindrome that begins with a given string $S$ | $O(\lvert S\rvert^2)$: Enumerate suffixes and check palindromicity | $\Theta(\lvert S\rvert)$: Use Knuth–Morris–Pratt w.r.t. reversed $S$ plus $S$ |
| #36 | Count digit 7's in positive integers $< n$ that are divisible by 11 or 13 | $\Theta(n \log n)$: Enumerate integers $< n$ and count the digits | $\Theta(\log n)$: Design a dynamic programming over digits |
| #40 | Check if a list $l$ has three distinct elements that sum to 0 | $O(\lvert l\rvert^3)$: Enumerate triples in $l$ and check their sums | $O(\lvert l\rvert^2)$: Use a hash set and enumerate pairs in $l$ |
| #109 | Check if a list $a$ can be made non-decreasing using only rotations | $O(\lvert a\rvert^2)$: Enumerate the rotations of $a$ and check | $O(\lvert a\rvert)$: Check if the list $a$ has at most one inversion |
| #154 | Check if any rotation of a string $b$ is a substring of a string $a$ | $O(\lvert b\rvert^2\lvert a\rvert)$: Enumerate rotations and run string matching | $O(\lvert a\rvert + \lvert b\rvert)$: Run the suffix automaton of $a$ w.r.t. $b+b$ |

## TAKEAWAYS

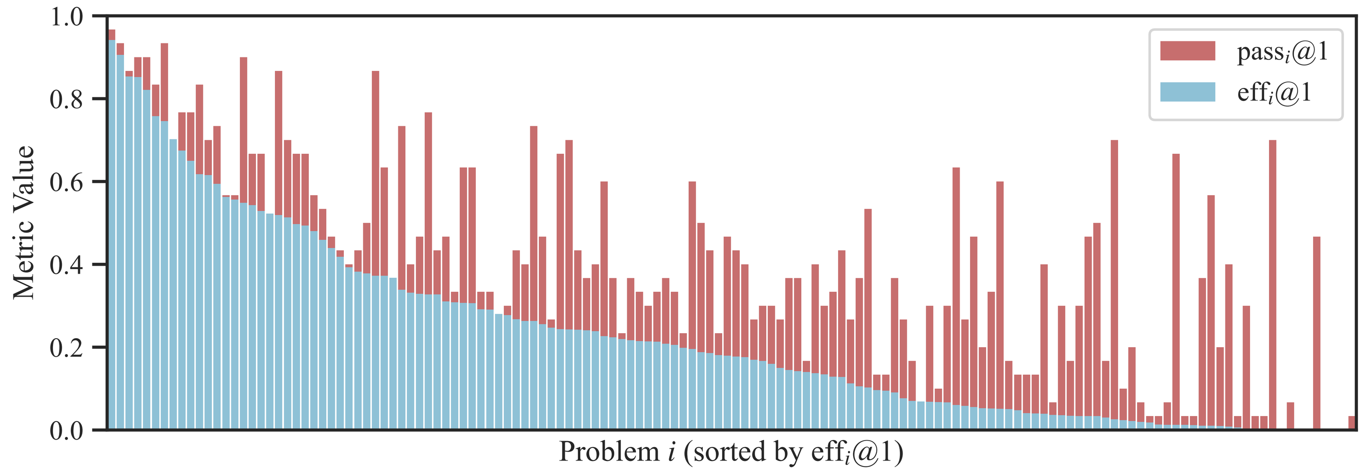
- **Overall evaluation results:** (*table truncated*)
  - Even strong LLMs **fall short** of generating **expert-level** efficient code.

| Model | Greedy | | Sampling | | | | | |
|---|---|---|---|---|---|---|---|---|
| | eff@1 | pass@1 | eff@1 | pass@1 | eff@10 | pass@10 | eff@100 | pass@100 |
| GPT-4 Turbo | 0.470 | 0.796 | — | — | — | — | — | — |
| GPT-4 | 0.454 | 0.831 | — | — | — | — | — | — |
| Llama 3 70B Instruct | 0.421 | 0.746 | 0.438 | 0.747 | 0.526 | 0.836 | 0.575 | 0.880 |
| Llama 3 8B Instruct | 0.344 | 0.592 | 0.345 | 0.564 | 0.500 | 0.770 | 0.595 | 0.874 |
| Mixtral 8x22B Instruct | 0.408 | 0.746 | 0.407 | 0.721 | 0.575 | 0.870 | 0.704 | 0.923 |
| Mixtral 8x7B Instruct | 0.266 | 0.444 | 0.279 | 0.456 | 0.436 | 0.689 | 0.542 | 0.810 |
| Claude 3 Opus | 0.401 | 0.789 | — | — | — | — | — | — |
| Claude 3 Sonnet | 0.345 | 0.662 | 0.365 | 0.677 | 0.498 | 0.814 | 0.594 | 0.887 |
| Claude 3 Haiku | 0.386 | 0.739 | 0.382 | 0.730 | 0.478 | 0.831 | 0.529 | 0.861 |
| Phind Code Llama V2 | 0.394 | 0.683 | 0.372 | 0.638 | 0.584 | 0.862 | 0.723 | 0.935 |
| ChatGPT | 0.364 | 0.683 | 0.374 | 0.673 | 0.557 | 0.847 | 0.690 | 0.937 |
| Code Llama 70B Python | 0.264 | 0.500 | 0.082 | 0.177 | 0.326 | 0.610 | 0.614 | 0.908 |
| Code Llama 34B Python | 0.268 | 0.458 | 0.226 | 0.405 | 0.511 | 0.786 | 0.711 | 0.934 |
| Code Llama 13B Python | 0.216 | 0.408 | 0.204 | 0.372 | 0.487 | 0.732 | 0.714 | 0.899 |
| Code Llama 7B Python | 0.247 | 0.373 | 0.180 | 0.320 | 0.432 | 0.663 | 0.643 | 0.837 |
| StarCoder | 0.195 | 0.352 | 0.134 | 0.236 | 0.355 | 0.557 | 0.542 | 0.787 |
| CodeGen 16B | 0.169 | 0.310 | 0.122 | 0.219 | 0.326 | 0.512 | 0.536 | 0.761 |
| CodeGen 6B | 0.193 | 0.296 | 0.111 | 0.188 | 0.298 | 0.455 | 0.491 | 0.694 |
| CodeGen 2B | 0.153 | 0.254 | 0.098 | 0.168 | 0.264 | 0.389 | 0.421 | 0.602 |
| CodeT5+ 16B | 0.160 | 0.317 | 0.130 | 0.250 | 0.343 | 0.551 | 0.551 | 0.785 |

- **Evaluation on two subsets:** (*table truncated*)
  - LLMs **struggle** in designing advanced algorithms.
  - LLMs are largely **unaware** of implementation optimization.

| Model | Algorithm Design Subset | | | | | | Implementation Optimization Subset | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | eff@1 | pass@1 | eff@10 | pass@10 | eff@100 | pass@100 | eff@1 | pass@1 | eff@10 | pass@10 | eff@100 | pass@100 |
| Llama 3 70B Instruct | 0.246 | 0.660 | 0.306 | 0.749 | 0.359 | 0.750 | 0.404 | 0.791 | 0.497 | 0.869 | 0.551 | 0.920 |
| Llama 3 8B Instruct | 0.201 | 0.518 | 0.303 | 0.724 | 0.367 | 0.849 | 0.313 | 0.582 | 0.468 | 0.806 | 0.571 | 0.906 |
| Mixtral 8x22B Instruct | 0.225 | 0.635 | 0.363 | 0.837 | 0.470 | 0.900 | 0.376 | 0.783 | 0.556 | 0.914 | 0.686 | 0.947 |
| Mixtral 8x7B Instruct | 0.124 | 0.391 | 0.244 | 0.681 | 0.344 | 0.850 | 0.248 | 0.473 | 0.411 | 0.699 | 0.515 | 0.827 |
| Claude 3 Sonnet | 0.184 | 0.577 | 0.328 | 0.804 | 0.450 | 0.950 | 0.358 | 0.723 | 0.475 | 0.846 | 0.548 | 0.893 |
| Claude 3 Haiku | 0.149 | 0.692 | 0.208 | 0.752 | 0.266 | 0.775 | 0.360 | 0.772 | 0.465 | 0.889 | 0.513 | 0.923 |
| Phind Code Llama V2 | 0.185 | 0.554 | 0.353 | 0.789 | 0.401 | 0.849 | 0.351 | 0.712 | 0.567 | 0.901 | 0.732 | 0.968 |
| ChatGPT | 0.120 | 0.488 | 0.304 | 0.799 | 0.483 | 0.950 | 0.337 | 0.715 | 0.508 | 0.864 | 0.633 | 0.949 |
| Code Llama 70B Python | 0.018 | 0.100 | 0.129 | 0.519 | 0.402 | 0.950 | 0.076 | 0.181 | 0.294 | 0.627 | 0.589 | 0.920 |
| Code Llama 34B Python | 0.071 | 0.293 | 0.271 | 0.713 | 0.425 | 0.881 | 0.197 | 0.415 | 0.473 | 0.804 | 0.687 | 0.949 |
| Code Llama 13B Python | 0.058 | 0.212 | 0.276 | 0.665 | 0.478 | 0.844 | 0.176 | 0.405 | 0.476 | 0.784 | 0.715 | 0.928 |
| Code Llama 7B Python | 0.068 | 0.202 | 0.231 | 0.589 | 0.393 | 0.761 | 0.165 | 0.349 | 0.417 | 0.703 | 0.620 | 0.863 |

- **Distribution of problem difficulties:**
  - High $\mathrm{pass}_i@1$, low $\mathrm{eff}_i@1$: *seemingly* easy task, **non-trivial** algorithm.

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