ByteAsk: Build-Aware Context and a Checking Harness for C++ Coding Agents

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Code and tasks: github.com/ByteAsk/byteask-system-cpp

Abstract

Large language model (LLM) coding agents have changed how people write software: a developer describes a change in plain language and the agent finds, edits, and tests the code. Most of this progress, however, has concentrated on a few widely used languages, Python above all. C and C++, which still underpin operating systems, browsers, databases, and embedded software, remain far less explored, even though their large, build-dependent codebases are exactly the setting in which agents struggle to find where a change belongs. We propose ByteAsk, a coding agent built for C and C++. At its core is a context engine that understands a codebase the way the project's own build does. Before the model starts, the engine tells it where the change belongs, which related places may need the same change, and which tests cover them; ByteAsk then checks the change against only those tests. We compare ByteAsk with OpenAI's Codex CLI running the same underlying model, on recent issues from popular and little-known C++ projects and on a small set of hard issues. Both agents fix the same number of runs in every set (129 of 144 each, across the two main sets), but ByteAsk uses 63–80% fewer tokens and costs 59–70% less.

1 Introduction

Coding agents now fix real issues in real projects, but in C and C++ much of their effort goes into finding where to work rather than into the fix. The meaning of a line of C++ depends on the build. Whether `book.apply(msg)` calls one overload or another, a template specialisation, or a function generated by a macro depends on include paths, macros, language options and conditional compilation, all of which differ from one build configuration to the next [6]. Text search sees none of this: it returns every function with the right name, every disabled `#if` branch and every unused overload, and leaves the model to sort them out by reading.

A fix is also rarely in one place. A bug in one function often has siblings: the same pattern in an overload, a specialisation for another type, a parallel code path for another platform, or a declaration and its tests that must change together. An agent that finds the first place and stops leaves the rest broken; an agent that searches for all of them reads large parts of the project to do so. Checking a change is just as costly: building a large C++ project and running its whole test suite takes minutes, so agents either skip the check or pay for it in time and tokens.

The result is that a general coding agent spends most of its model calls and tokens searching, reading and rebuilding. Those tokens are the main cost of running an agent, and they grow with the size of the project. ByteAsk is built to move that work out of the model's loop. We describe its approach (Section 2) and compare it with Codex CLI on the same model (Section 4).

2 The approach

ByteAsk is built on three ideas (Figure 1).

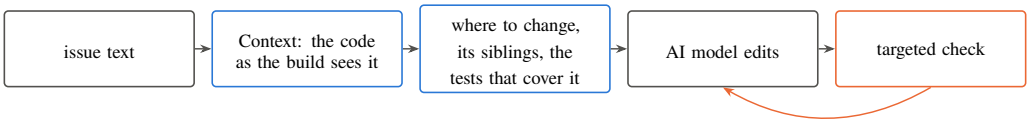


Figure 1: ByteAsk's approach. Before the model starts, Context identifies where the change belongs, which related places may need the same change and which tests cover them; the model edits, and a check limited to those tests confirms the change.

Understand the code as the build does. ByteAsk Context resolves names, overloads, templates, macros and conditional code for the project's actual build configuration, so a question about the code gets one precise answer rather than every textual match. It keeps that understanding current as the code changes.

Answer before the model asks. From the issue text alone, Context finds the places where a change most likely belongs, the sibling functions and related places that usually change with them, and the tests that exercise them. The model starts with that answer instead of searching for it, and can ask Context further questions as it works.

Check only what the change reaches. Instead of rebuilding the project and running every test, ByteAsk checks a change against the code and tests it actually reaches, so the model gets a fast, relevant answer on whether its fix works.

The aim is fewer turns spent searching and reading, fewer full builds, and so fewer tokens and lower cost for the same fixes.

3 How we compare

Both agents run GPT-6.1 Sol at medium reasoning effort with the same task prompt, a fresh clone and a fresh agent home per run, a 45-minute limit and the same resources (5 GB of memory, three CPUs); the two arms of a task start together. The prompt gives the issue text and a few rules: do not change the maintainers' test directories, keep the change focused, build the code and run the relevant tests, do not use the internet, and stop when done; the working tree is the answer. Codex CLI 0.164.0 runs as shipped against OpenAI's API. Context prepared each repository before the runs, and that time is not included in the run time. An issue is fixed when the agent's change, applied to a fresh copy of the repository, passes every fail-to-pass test and keeps every pass-to-pass test passing, offline. Token counts cover input (including cached input) and output; cost uses list prices; both include all of ByteAsk's own model calls. We report ratios of sums over paired runs. Each study's arms, task sets and analysis were written down before its runs. Savings are rounded down; a change is described as fewer or lower only when its 95% interval excludes zero, and the intervals are in the repository.

4 Results

Task sets. *Popular projects*: 23 issues from popular C++ projects, fixed in pull requests merged after the model's training cutoff; two runs each. *Little-known projects*: 49 issues from little-known C++ projects with real linked issues; two runs each. *Hard issues*: 5 issues from these pools that Claude Code failed, each run three times.

The same fixes at a fraction of the tokens and cost. Table 1 gives the results. Both agents fixed the same number of runs in every set, with no detected difference: 44 of 46 each on popular projects, 85 of 98 each on little-known projects (one run differs in each direction), 129 of 144 each pooled, and 9 of 15 each on hard issues. With the same fixes, ByteAsk used 63.9% fewer tokens on popular projects, 80.1% fewer on little-known projects and 80.8% fewer on hard issues, at an estimated cost that was 59.9%, 70.1% and 67.9% lower.

Table 1: ByteAsk vs Codex CLI, both GPT-6.1 Sol at medium effort, with the same number of runs fixed in every set (each: popular 44 of 46, little-known 85 of 98, pooled 129 of 144, hard 9 of 15). Values are means per run; savings are computed on sums over the paired runs. Tokens and cost include all of ByteAsk's own model calls. Hard issues: five tasks, three runs each.

			Tokens per run			Estimated cost per run	
Task set	Tasks	Runs	Codex	ByteAsk	Saving	Codex / ByteAsk	Saving
Popular projects	23	46	727k	263k	63.9%	$0.227 / $0.092	59.9%
Issues in little-known projects	49	98	2,296k	457k	80.1%	$0.456 / $0.137	70.1%
Both sets pooled	72	144	1,795k	395k	78.0%	$0.383 / $0.122	68.1%
Hard issues	5	15	2,085k	400k	80.8%	$0.441 / $0.142	67.9%

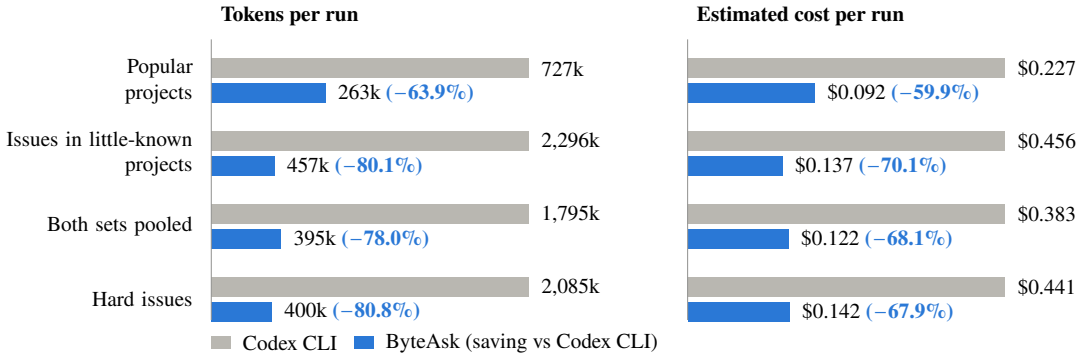


Figure 2: Tokens and estimated cost per run, Codex CLI beside ByteAsk, on the same model and tasks with the same number of runs fixed. Each row is scaled to Codex CLI (full length); the bold figure is ByteAsk's saving, computed on sums over the paired runs.

The savings are not driven by a few runs: ByteAsk used fewer tokens than Codex CLI in 143 of the 144 paired runs of the two main sets and cost less in 144 of them (Figure 2).

Where the savings come from. ByteAsk made 33.7% fewer model calls than Codex CLI on popular projects, 62.3% fewer on little-known projects and 67.2% fewer on hard issues (Table 2). This is consistent with the likely places and their code arriving in the first turn, so the model has less to search and read, and with a targeted build standing in for full builds. Each call also carried fewer tokens on average. Over the 144 paired runs of the two main sets, each fixed issue cost $0.427 with Codex CLI and $0.136 with ByteAsk.

5 Related work

Most agents locate code by searching and reading [9, 11], an approach Anthropic's guidance for coding agents prefers over precomputed retrieval, while noting that hybrids often work best [8]; others retrieve code [12] or explore repository graphs [1, 3, 5, 7]. ByteAsk instead works from the code as the configured build sees it and delivers its answer before the model asks. Harness design alone changes results [2, 10, 13], and agent evaluations should report cost alongside accuracy [4].

6 Conclusion

ByteAsk combines a build-aware understanding of C++ code with a first-turn answer and targeted checks. On the same model as Codex CLI, it fixed the same number of runs with 63–80% fewer tokens and 59–70% lower estimated cost.

Table 2: Estimated cost per fixed run and model calls per run, Codex CLI beside ByteAsk, for the same runs as in Table 1.

Task set	Cost per fixed run, Codex / ByteAsk	Model calls per run, Codex / ByteAsk	Fewer model calls
Popular projects	\$0.237 / \$0.096	19.6 / 13.1	33.7%
Issues in little-known projects	\$0.525 / \$0.158	41.1 / 15.5	62.3%
Both sets pooled	\$0.427 / \$0.136	34.2 / 14.7	57.1%
Hard issues	\$0.735 / \$0.236	36.8 / 12.1	67.2%

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