

Cross-Benchmark Transfer from RL on Agentic Coding Tasks

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Assessment. The paper itself. Every figure in this edition comes from its own abstract, read on the arXiv abstract record. The HTML full text was rate-limited by the fetch proxy during this run, so no affiliation is attributed and no figure outside the abstract is used.

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Abstract (verbatim)

Coding agents often fail in the last mile: they build most of a feature but drop a requirement, test only the cases their implementation already handles, break behavior that was supposed to stay intact, or validate against an unchecked assumption. We ask whether reinforcement learning (RL) on expert-built agentic coding tasks closes this gap, and whether what the agent learns transfers beyond the training distribution. We post-train Kimi K2.7 Code, a 1T-parameter (32B active) open-weight mixture-of-experts model, with RL alone on 1,700 tasks: 1,000 repository tasks graded by hidden fail-to-pass tests and by pass-to-pass tests of existing behavior, and 700 terminal tasks graded by expert-written hidden verifiers. The reward is the fraction of target checks passed and drops to zero if any pass-to-pass test fails. One epoch of GSPO on a rank-32 LoRA adapter improves pass@1 on each of the six external benchmarks we evaluated, across three agent harnesses: SWE-Bench Pro (60.1 to 64.8), DeepSWE (31.0 to 43.4), Terminal-Bench 2.1 (67.4 to 82.0), Terminal-Bench 3 (1.4 to 12.1), Terminal-Bench 4 (0.0 to 7.6), and SWE-Marathon (5.0 to 25.0). Pooled over the five independent task sets (Terminal-Bench 4 revises Terminal-Bench 3), the improvement is significant ($p < 0.001$), and it remains significant on the three sets released after the training data was collected ($p = 0.004$); the model also improves under both harnesses never used in training. Median trajectories on DeepSWE and Terminal-Bench 3 are 24-35% shorter in agent

steps. The base model's failed DeepSWE runs are mostly near-misses, and on the tasks the trained model newly solves, paired trajectories show it avoiding each of the four failure modes above.

Notes taken during verification

- Identifier verified before any figure was used: the YYMM 2610 is consistent with a 1 October 2026 submission and the title matches the story. No adjacent record was used.
- The 0.0 -> 7.6 (Terminal-Bench 4) and 1.4 -> 12.1 (Terminal-Bench 3) pairs start from a floor.

They are reported, but the edition leans on the pooled significance, not on these two.

- The paper's own significance claim is pooled over five independent task sets, with a separate

$p = 0.004$ for the three sets released after the training data was collected.