

# Autonomous Issue Resolver: Towards Zero-Touch Code Maintenance

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## Abstract

Recent advances in Large Language Models have revolutionized function-level code generation; however, repository-scale Automated Program Repair (APR) remains a significant challenge. Current approaches typically employ a control-centric paradigm, forcing agents to navigate complex directory structures and irrelevant control logic. In this paper, we propose a paradigm shift from the standard Code Property Graphs (CPGs) to the concept of Data Transformation Graph (DTG) that inverts the topology by modeling data states as nodes and functions as edges, enabling agents to trace logic defects through data lineage rather than control flow. We introduce a multi-agent framework that reconciles data integrity navigation with control flow logic. Our theoretical analysis and case studies demonstrate that this approach resolves the "Semantic Trap" inherent in standard RAG systems in modern coding agents. We provide a comprehensive implementation in the form of *Autonomous Issue Resolver (AIR)*, a self-improvement system for zero-touch code maintenance that utilizes neuro-symbolic reasoning and uses the DTG structure for scalable logic repair. Our approach directly addresses the core limitations of current AI code-assistant tools and tackles the critical need for a more robust foundation for our increasingly software-dependent world.

## 1 Introduction

In the 21st century, software engineering has evolved from a niche discipline into the digital backbone of the global economy, generating trillions in value and employing hundreds of millions of people worldwide. Today, software is the invisible infrastructure that connects commerce, communication, healthcare, transportation, and nearly every facet of modern life. It has become the omnipresent, global aether of our digital civilization. But unlike a fundamental force of nature, software is created by humans, inheriting our limitations and tendency to make mistakes.

The early days of software developed by smaller teams are long gone. Today's software products are huge, often comprising millions of lines of code and hundreds of dependencies. No single human, nor even large teams, has a comprehensive understanding of such systems. This is the same as trying to build a skyscraper with bare hands. Current development methodologies attempt to manage this complexity by breaking down the problems, but this merely distributes the potential failures among developers. This is because individual developers, working on isolated components, still introduce bugs, inconsistencies, and architectural drift. The consequences are significant: costly delays, security vulnerabilities, system outages, and a drag on innovation. Industry reports consistently highlight that debugging and maintenance consume a staggering 50-70% of development resources [1].

The path to truly reliable software lies in systematically reducing the dependence on manual intervention for repetitive, error-prone, and complex analytical tasks. AI-based automation offers the potential for consistency, speed, and depth of analysis that exceed human capabilities. By automating many stages of the software development lifecycle (SDLC), from code generation and testing to debugging and refactoring, we can mitigate human error, enforce best practices, and achieve unprecedented levels of quality assurance.

The core blocker for zero-touch maintenance is not *code generation*, but *systemic reasoning*: mapping an *issue* to a *minimal, safe* set of edits under repository-wide constraints (APIs, invariants, tests, deploy rules). This demands (i) a *repository-scale semantic representation* (beyond embeddings alone), and (ii) a *risk-aware control policy* that decides when to stop, where to edit, and how to validate.

Modern models can synthesize non-trivial patches and reason about code structure, yet this progress has not translated into robust performance on realistic repository-level tasks: on benchmarks such as SWE-bench, resolution rates remain modest, especially for open-source models.

We refer to this gap as the *context crisis* of repository-scale APR. At small scales, LLMs can be given all relevant code in a single prompt. At repository scale, however, the model must operate under strict context limits while the bug’s cause and manifestation are separated across files, layers, and abstractions. Existing tools address this by improving retrieval and by adding agentic planning, but they leave the underlying representation of the repository largely unchanged: a directory of files, occasionally augmented with control-centric graphs.

We argue that this file-first, control-centered view is misaligned with the causal structure of many real-world bugs and how the development is done in the real world. Human developers rarely debug or write new code by reading files. Instead, they trace the *flow of data*, following a specific object or variable as it is transformed and routed through the system. We propose to make data-first mental model explicit and to turn it into the primary substrate on which a LLM-based repair agent lives.

Our approach has demonstrated good results on several SWE benchmarks, reaching a resolution rate of 87.1% on SWE-Verified benchmark.

The main contributions of this work are as follows:

- We introduce the *Data-First Transformation Graph* (DTG), a data-centric representation of software repositories that performs a semantic compression of Code Property Graphs and aligns with human debugging strategies.
- We establish connections between the DTG, data-centric optimization frameworks, and Reinforcement Learning, motivating a learning regime in which LLMs reason over graph structure.
- We propose a novel architecture of the DTG-based repair agent and analyze its performance and accuracy on several benchmarks.

## 2 Problem Overview and Background

The idea of using AI-based automation in software development is not novel, and there are quite a few products. Tools such as GitHub Copilot, Amazon Code Whisperer, Tabnine [2], Cursor [3], and various chatbot assistants (such as specialized extensions of Claude Code or ChatGPT) are popular today and represent the current state of the art (see also Appendix, Table B.2). Most existing products are iterating on developer help.

Table B.2 separates *professional*, *basic*, and *specialized* offerings. Professional tools optimize *ergonomics* for humans-in-the-loop (IDE integration, fast completions), but remain fundamentally

Table 2.1: Capability taxonomy: where existing tools help - and where they fall short for autonomous maintenance. We classify existing tools by their primary interaction model and identify the specific limitations that prevent them from achieving zero-touch maintenance.

Category	Typical Features	Limits for Maintenance
Completion / Suggestion	Next-line blocks, boilerplate, refactors	Local context only; no global impact modeling; no gating against risk.
Conversational Dev Assist	Explain, edit, diagnose from chat	Quality depends on prompt curation; inconsistent across large repos.
Repo Search & Retrieval	Embedding search, code Q&A, cross-ref	Weak semantics beyond lexical/embeddings; limited data-/control-flow.
Automated Program Repair (APR)	Patch synthesis for unit-failing bugs	Often single-hunk fixes; brittle across multi-file causal chains.
Test Generation	Unit/integration test synthesis	Improves coverage, but does not plan changes or manage regressions.
Agentic Tool Use	Editors, terminals, CI tools via agents	Without risk-aware policy, tends to oscillate or over-edit.

*reactive* and local in scope. Basic tools accelerate *scaffolding* and prototyping, yet rarely manage repository-scale dependencies or change risk. Specialized systems reach *SOTA* in narrow settings (e.g., competitive programming or algorithm discovery), but are not designed for end-to-end maintenance workflows.

## 2.1 Limitations of existing tools

Current LLM-based agents such as SWE-Agent and OpenHands typically interact with repositories through a file-system interface: they list directories, open files, and issue search commands. Each action consumes context and forces the model to maintain a growing internal representation of control and data dependencies. As repositories grow, this misalignment becomes the main bottleneck: the model "thinks" at the level of dataflow but sees the world as files and control structures.

Retrieval-Augmented Generation (RAG) is the standard strategy for scaling LLMs to large corpora. In code domains, RAG usually combines lexical search with dense embeddings of code snippets. For task prompts involving a particular entity (e.g., fixing some issue that involves a `User` class), the system retrieves semantically similar snippets for the model to condition on.

However, semantic similarity is not the same as *causal* relevance:

- If a bug involves corrupt user IDs, a vector search for `User` will fetch class definitions, UI components, and schema migrations but may miss a generic sanitizer function that silently strips or hashes IDs without ever mentioning the word "user".
- In data pipelines, failures may be caused by a shared transformation used across multiple domains. Semantically similar code may not share causal influence on the failing data.

This is becoming increasingly common in modern codebases which are often use loose-coupling design patterns when the code tends to live in semantically disconnected clusters of functions which are not called directly (e.g. aspect-oriented programming, dependency injection, and so on).

Traditional RAG treats code as an unordered bag of textual fragments. Even graph-based retrieval (e.g., GraphRAG) typically uses graph structure only to improve retrieval quality, not as

the state space in which the agent itself moves. The agent still *lives* in the file system, reading linearized text.

### 3 Related Work

The introduction and further development of Transformer-based models trained on large code corpora has revolutionized software engineering. Early breakthroughs like Codex [4] and AlphaCode [5] demonstrated that models could synthesize functional code from natural language descriptions. These foundational models power a generation of interactive assistants, including GitHub Copilot [6], Amazon CodeWhisperer [7], and Cursor [8]. While effective for local, "next-block" completion [2], these tools primarily operate as "copilots," relying on the human developer to manage the broader repository context and verify correctness.

Agentic frameworks such as ReAct [9] and Reflexion [10], allowed LLMs to plan, execute tools, and observe outputs. State-of-the-art systems like SWE-agent [11] and OpenHands [12] utilize these patterns to interact with repositories via shell commands and file editors, and currently often used as solid baselines. Similarly, AutoCodeRover [13] employs abstract syntax tree (AST) analysis to improve fault localization.

However, these agents largely treat the repository as a file system to be searched and read, a "file-first" perspective that suffers from inefficiency when bugs span multiple abstraction layers. Recent evaluations on benchmarks like SWE-bench [14, 15] indicate that while agents can solve isolated tasks, they struggle with long-horizon reasoning required for enterprise issues [16]. Claude Code [17] and LocAgent [18] attempt to mitigate this by improving retrieval and localization, yet they still fundamentally operate on text-based or partially structured representations that do not explicitly model data lineage.

Since the search over codebase is essentially a search over unstructured data, it was natural to employ the graph-based methods for localization of relevant snippets of code. The Code Property Graph (CPG) [19] unified ASTs, control-flow graphs (CFGs), and program dependence graphs (PDGs) into a single structure, primarily for vulnerability discovery.

Recent efforts have attempted to integrate such graphs with LLMs to improve repository understanding. CodexGraph [20] and RepoGraph [21] utilize graph databases to enhance Retrieval-Augmented Generation (RAG) by capturing dependencies between files and functions. The Code Graph Model (CGM) [22] similarly integrates graph structures to aid in logical reasoning. However, these approaches often retain the "representation bloat" of standard CPGs or focus on improving retrieval recall rather than navigation that mimics the "operational reasoning". Unlike these control-centric models, our approach utilizes a Data-First Transformation Graph (DTG), which compresses the topology to focus on data states and transformations, aligning somehow our approach with the "flow-based" mental models used in high-performance computing optimization.

Although most current agents rely on prompt engineering and in-context learning, Reinforcement Learning (RL) has shown promise in discovering novel strategies in complex domains. Deep-Mind's work on AlphaZero [23] and subsequently AlphaDev [24] demonstrated that RL agents could discover algorithms that outperform human-written implementations. In the domain of program repair, early learning-based systems like Getafix [25] mined fix patterns from static analysis. More recently, AlphaEvolve [26] pushes this further by evolving code structures. Our work incorporates an RL-driven control policy to navigate the DTG, distinguishing AIR from purely prompt-driven agents by allowing it to learn stopping conditions and navigation strategies that minimize regression risks. We are using a simple DQN-based online learning. Note that RL is not a key element of our algorithm, and it can be replaced by simple Monte Carlo Tree Search style graph traversing.

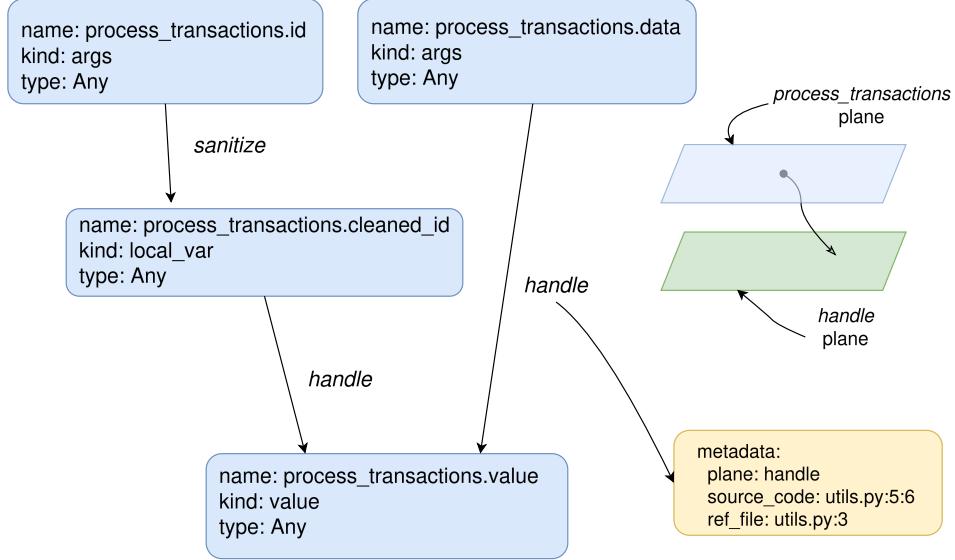


Figure 4.1: The partial visualization of the multi-dimensional Data Transformation Graph for a snippet of code. Nodes contains full description of processed data. Edges are effectively transformation functions (*sanitize*, *handle*)

## 4 Methodology

### 4.1 A data-first graph representation

We propose a fundamental re-architecture of the agent's environment. Rather than representing a repository as text files, or even as a multi-layer code property graph in which functions and statements are the primary nodes, we focus directly on the *data* that flows through the system.

We define the *Data-First Transformation Graph* (DTG) as a directed multigraph with:

- **Nodes as data states:** Each node corresponds to a semantically meaningful data artifact (e.g., a variable, object, etc) at a specific point in its lifecycle, annotated with type, schema, constraints, and source locations.
- **Edges as transformations:** Each edge corresponds to an operator, function, or API call that transforms one data state into another, potentially guarded by control-flow conditions.

To illustrate this concept, consider the following snippet of code that implements a toy transaction handle. Figure 4.1 depict a simplified DTG for this code.

```

1  utils.py
2  def process_transactions(id, data):
3      cleaned_id = sanitize(id)
4      return handle(cleaned_id, data)
5
6  def handle(cleaned_id, data):
7      print(f"processed {cleaned_id}")
8
9  def sanitize(id: Any) -> str:
10     id = str(int(id))

```

```

11     assert len(id) == 4, f"id: wrong length: {id}"
12     return id

```

This representation compresses away syntactic detail and control-flow noise, allowing the agent to traverse the "causal path" of a variable, effectively pruning irrelevant control flow and syntax noise that typically confuses. Conceptually, the repository ceases to be a library of documents and becomes a navigable network of data lineages.

## 4.2 Why Reinforcement Learning is crucial

The second key ingredient of our design is a smart integration of RL patterns. We draw inspiration from the successes of systems like DeepMind's AlphaGo and AlphaCode [23], [27], which demonstrated how machines can achieve superhuman performance in complex domains not just by mimicking data, but by learning optimal strategies through interaction and self-correction.

Unlike supervised learning (training on fixed code examples), RL allows the AI agent to learn by doing. It generates code, tests it (using automated test suites), observes the results (pass/fail, performance metrics, new bugs introduced) and receives feedback (rewards or penalties). This iterative loop enables the system to find correct and efficient code implementations that might not exist in any training dataset, to optimize code for specific goals, and to self-correct and self-improve. The latter is very important, because it effectively removes the slow human factor (which is the main bottleneck) and allows the system to learn exponentially. The RL loop is implemented in a quite straightforward way, via anchoring objective function to the unit tests

## 4.3 Why holistic reasoning is the key

An RL loop alone is insufficient if the agent cannot understand the code. Generating random code is inefficient, because the size of problem space (e.g. the number of possible variations of code snippet) is bigger than the number of particles in all multiverses combined. We need a powerful and scalable reasoning engine that provides the agent with a deep and structured view of the code base.

# 5 Algorithm details

The proposed data-first perspective sits at the intersection of several research lines: code property graphs and static analysis, data-centric optimization and flow-based programming, and graph-based + agentic approaches to LLM-driven software engineering.

## 5.1 Code property graphs and representation bloat

The Code Property Graph (CPG), popularized by tools such as Joern [28], unifies three classic program representations in a single multi-graph: abstract syntax trees (ASTs), control-flow graphs (CFGs), and program dependence graphs (PDGs). In principle, CPGs contain all information needed for both security analysis and program repair.

In practice, however, raw CPGs suffer from extreme representation bloat. The DTG can be viewed as a *semantic compression* of such graphs. By abstracting away AST and CFG nodes and focusing only on data states and the transformations between them, it adopts a "functions-as-edges" topology, in contrast to the "functions-as-nodes" topology of call graphs and many CPG formulations. This aligns the representation with the causal structure of dataflow, rather than the syntactic structure of the code.

## 5.2 Data-centric optimization and flow-based programming

In high-performance computing and compiler optimization, there has been a shift from control-centric intermediate representations (such as linearized IR or basic-block graphs) to data-centric views that emphasize movement and locality. Data-centric frameworks, such as Stateful Dataflow Multigraphs, treat computations as transformations on data streams and have demonstrated significant benefits in optimization and reasoning.

Similarly, flow-based programming (FBP) and ETL (Extract–Transform–Load) pipelines in data engineering model systems as graphs of black-box components connected by typed data channels. While this style is common in specialized domains, it has rarely been applied to general-purpose, object-oriented software in the context of defect localization and repair.

Our DTG formulation can be seen as importing these data-centric ideas into APR. The repository is treated as a large, heterogeneous dataflow graph in which "nodes" are not operators but states, and "edges" encapsulate black-box transformations.

## 5.3 Agentic navigation on graphs

Context Agent treats the DTG as the world itself. The agent's state is a node (or small subgraph), its primitive actions are graph traversals and inspections, and its perception is restricted to a local neighborhood. Moving the agent "body" into the graph opens up new strategies for search, planning, and exploration based on graph theory and dataflow, rather than ad-hoc file navigation.

## 5.4 The Data-First Transformation Graph

To formalize the Data-First Transformation Graph (DTG) we introduce first some definitions.

### 5.4.1 Formal definition

Let a software repository  $\mathcal{R}$  be represented as a directed multigraph

$$\mathcal{G}_{\text{DTG}} = (V, E),$$

where  $V$  is a set of vertices (data states - see below) and  $E$  is a set of edges (transformations).

Each vertex  $v \in V$  represents a data state: a specific variable, object, or data artifact at a particular semantic stage. Compared with classical data-flow graphs, DTG nodes are enriched with semantic metadata, not merely variable names.

Each vertex  $v$  carries:

- **name:** A unique identifier, e.g., `module.func.var`.
- **kind:** Class of data, e.g. is it the argument of function, a global variable, or constant, etc.
- **type:** Its static or inferred language-level type, e.g., `List[int]` or `torch.Tensor`.
- **schema:** For structured objects, a description of fields and their types (e.g., `{id:int, name:str}`).
- **constraints:** Symbolic constraints known at this point, such as shape information or invariants (e.g., `shape = (3, 224, 224)`).
- **metadata:** Source-level metadata, including file path, function, and line span.

This information can be partially obtained from static analysis (e.g., SSA form, type inference) and partially hypothesized or refined by the LLM during exploration.

### 5.4.2 Edge set: transformations

Each edge  $e_{i \rightarrow j} \in E$  represents a transformation from data state  $v_i$  to data state  $v_j$ . An edge exists when there is a concrete operation in the repository that takes the value at  $v_i$  and produces the value at  $v_j$ .

Edges are annotated with:

- **plane:** A reference to the view plane that represents on some level of abstraction the transformation, e.g., a function call, and so on.
- **source, ref\_file:** Reference points to definition and points of invocation, respectively.
- **semantics:** An optional natural-language summary of the transformation’s intent, generated and iteratively refined by the LLM (e.g., “increments a counter”, “normalizes a tensor”).

## 6 Graph construction pipeline

Constructing the DTG is the most technically demanding phase. We use a “lazy-loading” pipeline that combines static and dynamic information.

**Core parser: Tree-sitter and ast:** Tree-sitter [29] provides incremental, multi-language AST parsing for languages such as Python, Java, JavaScript, and C++. We use it to:

- Extract variable declarations, assignments, and function definitions,
- Identify function calls and their arguments,
- Recover control-flow constructs for guard extraction.

Custom Tree-sitter queries (in `.scm` files) define language-specific patterns for these elements [29], but the downstream DTG schema is language-agnostic. Rather than directly exposing the full internal graph of these tools to the LLM, we project only the data-state and transformation information needed for DTG navigation. We use a `neo4j` graph database as persistent storage and efficient indexing over node and edge attributes.

### 6.1 Agent environment

We model agents whose internal state is a structured view over the DTG.

**State schema.** A minimal typed state can be defined as:

```
1 class AgentState(TypedDict):
2     current_node_id: str
3     visited_nodes: List[str]
4     hypothesis: str
5     graph_view: SubGraph # local neighborhood around current_node_id
```

The `graph_view` restricts the visible graph to a bounded-radius neighborhood around the current node, which is passed to the LLM at each step.

**Tools (action space).** The agent is equipped with a small set of graph-oriented tools (Table 6.2). These tools abstract away file-system operations and present the agent with a clean graph navigation API.

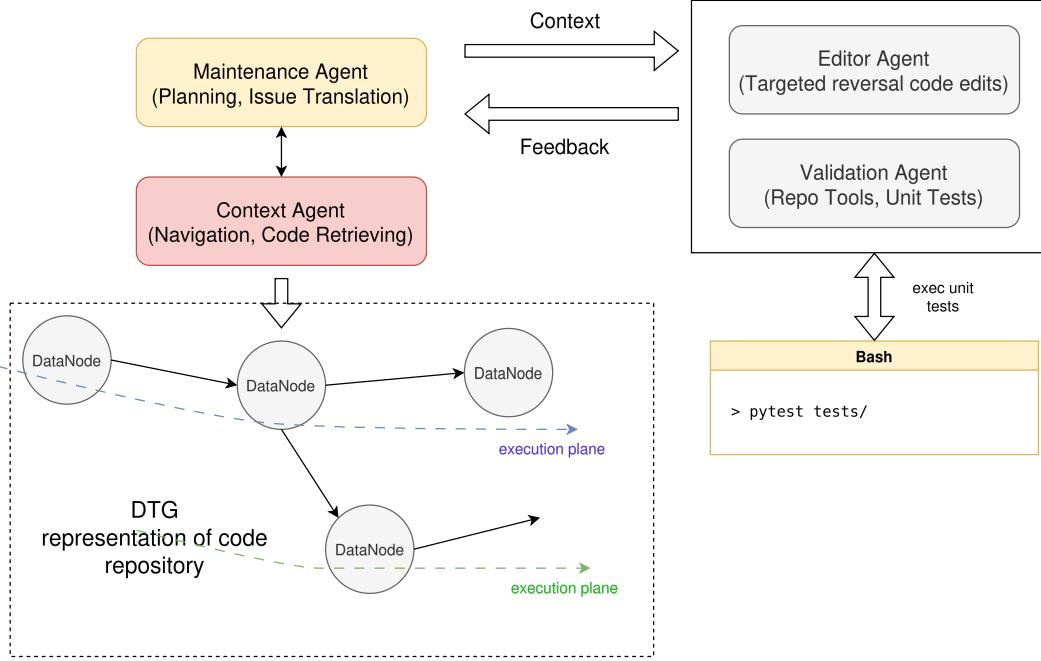


Figure 6.2: The AIR Multi-Agent Architecture. The system employs a decoupled "Plan-Navigate-Execute" loop to manage context window limitations. The Context Agent (pink) operates exclusively within the graph domain to localize faults without reading file content. Once the fault subgraph is identified, the Maintenance Agent (yellow) formulates a high-level repair plan, which is translated into concrete syntax edits by the Editor Agent (gray). This separation prevents the "Semantic Trap" by ensuring the planner is conditioned only on causally relevant data lineages rather than raw repository noise.

## 7 High-Level Architecture (Product)

The design of the competitive AI tool for autonomous code development requires careful consideration of its integration into existing developer workflows and ecosystems. This section details the rationale behind our core architectural decisions: adopting a frontless application model and pursuing deep integration with Git service platforms.

### 7.1 Why We Designed a Frontless Application

The primary goal of our AI product is to enhance and automate the software development lifecycle, particularly within Continuous Integration and Continuous Deployment (CI/CD) pipelines, to accelerate development efforts.

Modern software development heavily relies on automated CI/CD pipelines. These pipelines are inherently process-driven, triggered by events like code commits or pull requests, and often operate without direct human interaction. Unlike tools designed for interactive use (such as IDE plugins or code editors), our product aims to perform complex tasks with minimal or zero real-time human guidance once configured. The "interface" becomes the configuration files and the standard platform mechanisms for feedback (PR comments, commit statuses, logs). This aligns with the concept of "Invisible Computing" or "Calm Technology," [30] where technology recedes into the background, providing value without demanding constant attention.

Function Signature	Description
<code>navigate(direction= "upstream"   "downstream")</code>	Move along incoming or outgoing edges from the current node, updating <code>current_node_id</code> .
<code>inspect_data()</code>	Return metadata (type, schema, constraints, context) for the current node.
<code>read_transformation(target_node_id)</code>	Return code associated with the edge from the current node to <code>target_node_id</code> .
<code>run_test(test_id)</code>	Execute a test case, optionally with dynamic taint tracking, and overlay the resulting execution trace onto the DTG.

Table 6.2: Available Navigation and Testing Functions

Headless systems are often easier to scale and integrate via APIs and webhooks. Our AI can be deployed as a service that listens for events from multiple repositories or projects simultaneously, processing tasks asynchronously. This architecture is well-suited for organizational-level adoption where the tool needs to operate across numerous CI/CD pipelines.

## 7.2 On the Importance of Platform

While a frontless architecture defines *how* the user interacts (or does not directly interact) with our tool, *where* the tool operates is equally critical. Deep integration within established Git service platforms such as GitHub and GitLab is our primary technical and business strategy.

Platform integration allows our AI to become a native participant in the core developer workflow – the Pull/Merge Request process. It can be triggered automatically by platform events (PR opened, commit pushed, comment posted), perform its analysis and code generation, and report results directly back into the platform interface (e.g., posting PR comments with suggestions, pushing code changes to the PR branch, updating status checks). Our tool operates autonomously and asynchronously, typically after the initial code has been written (Figure 7.2)

There is another, more subtle reason to build a platform app rather than a standalone one: platforms like GitHub and GitLab offer rich ecosystems. Integration allows our tool to potentially interact with other tools and services operating within the same platform. This creates opportunities for more powerful, composite automation, and sometimes this alone is valued much more than just a yet another fancy tool for code generation.

## 7.3 Distinction from Interactive Code Assistants (e.g., GitHub Copilot)

Interactive assistants like GitHub Copilot primarily focus on augmenting the developer during the act of writing code within the IDE. They operate synchronously, responding to immediate prompts and context within the editor. Our tool operates autonomously and asynchronously, typically after the initial code has been written, focusing on broader, process-oriented tasks within the development life-cycle (e.g., automated refactoring based on PR feedback, generating tests for a new feature branch, ensuring code adheres to project-wide patterns).

Copilot assists the individual developer's coding speed; our tool automates team and process workflows, operating at the level of commits, branches, and pull requests within the platform.

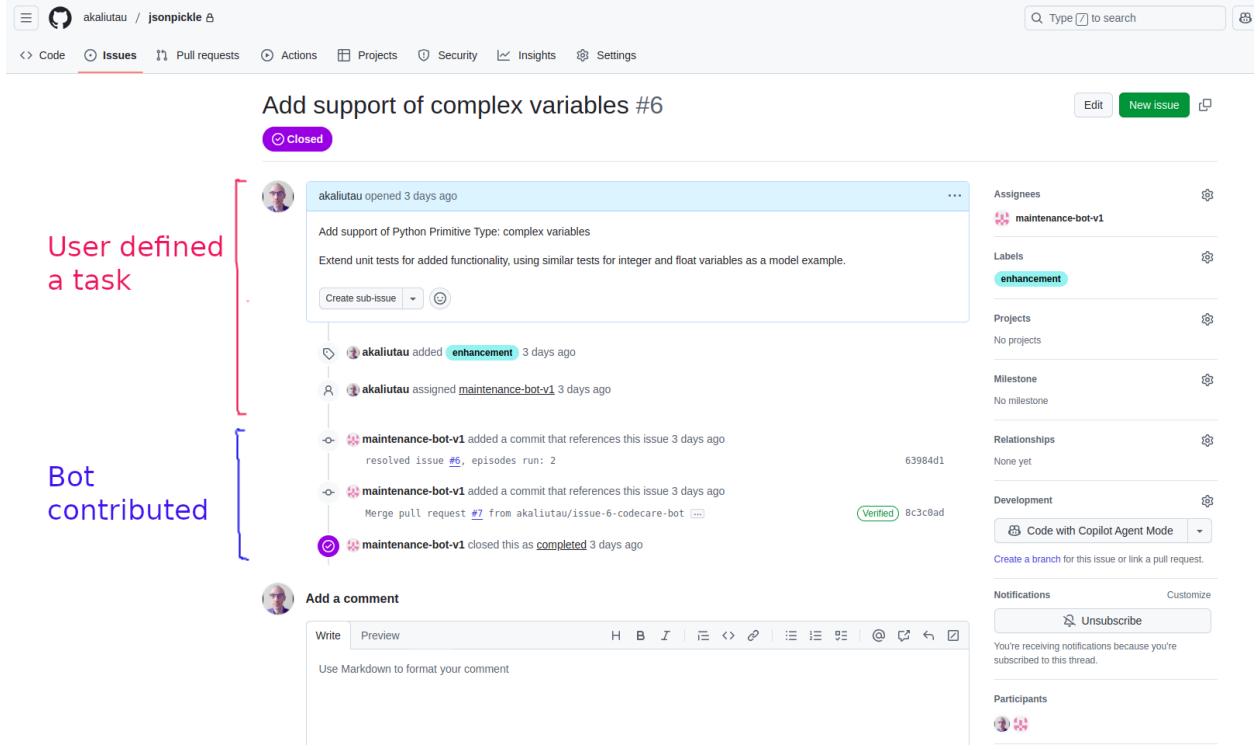


Figure 7.3: Our product leverages the existing GitHub platform and workflows (Issues, Branches, PRs). There is no need for developers to learn new tools or interfaces. The Bot acts like another member of the team, communicating and contributing via established mechanisms. Such approach does not break existing automation. Note, that human developers can still review the Bot’s code changes directly within the PR interface, leave comments, or request modifications if needed. This step maintains human oversight where desired.

## 8 Experiments and Benchmarks

Evaluating the performance of AI systems designed for complex, autonomous tasks (such as software development) presents unique challenges. Unlike traditional software, where deterministic output is expected, AI systems often exhibit variability and rely on complex internal behavior.

### 8.1 Benchmarks and Metrics

To test our tool we use the following benchmarks.

**SWE-bench family.** To test the data-first hypothesis, we outline an evaluation protocol focusing on repair effectiveness, localization efficiency, and context utilization. We evaluate on the SWE-bench suite (*Full*, *Verified*, *Lite*; using metric: *%Resolved with repository tests*) [31, 15].

**APR.** QuixBugs (Java/Python) [32] and HumanEvalFix.

**Industrial tickets.** A stratified sample of  $N$  internal issues across the services.

**Primary metrics:** *%Resolved* (tests pass), MTTR (hours), regression rate (%), reviewer effort (minutes/patch), CI cost (compute \$), and change risk score (static+dynamic).

Table 8.3: Github repositories used in our tests. Total issues column indicates the number of reported issues in repository, snapshot of 12/05/2025

Repository	URL	Stars	Total Issues	Selected Issues	Complexity
jsonpickle	<a href="https://github.com/jsonpickle/jsonpickle">https://github.com/jsonpickle/jsonpickle</a>	1.3k	62	10	low
arrow-py	<a href="https://github.com/arrow-py/arrow">https://github.com/arrow-py/arrow</a>	8.9k	87	10	low
flashtext	<a href="https://github.com/vi3k6i5/flashtext">https://github.com/vi3k6i5/flashtext</a>	5.7k	59	10	low
requests	<a href="https://github.com/psf/requests">https://github.com/psf/requests</a>	53.4k	203	10	low
poetry	<a href="https://github.com/python-poetry/poetry">https://github.com/python-poetry/poetry</a>	33.9k	518	10	medium
Pillow	<a href="https://github.com/python-pillow/Pillow">https://github.com/python-pillow/Pillow</a>	13.2k	67	10	high
python-qrcode	<a href="https://github.com/lincolnloop/python-qrcode">https://github.com/lincolnloop/python-qrcode</a>	4.2k	42	10	low
tinydb	<a href="https://github.com/msiemens/tinydb">https://github.com/msiemens/tinydb</a>	7.4k	20	10	medium
urllib3	<a href="https://github.com/urllib3/urllib3">https://github.com/urllib3/urllib3</a>	4k	134	10	medium
httpx	<a href="https://github.com/encode/httpx">https://github.com/encode/httpx</a>	14.8k	61	10	medium

## 8.2 Baselines

We employ the standard baselines, popular in coding tasks: SWE-agent [11], OpenHands [12], AutoCodeRover [13], and an ablated AIR without RL (AIR w/o RL) and without DTG. The numbers for the baselines are taken from the original papers and the benchmark website. [31]

## 8.3 Compute Budget and Settings

Uniform wall-clock budget per issue (e.g., 60–120 minutes), identical tool access, and fixed seeds. We report median over three runs and 95% CIs.

## 8.4 Close-to-life experiment

On the top of classic benchmarks, we simulated a realistic scenario, where the AI agent is tasked with resolving reported software issues and its output is reviewed by a professional engineer. We selected 10 open-source Python repositories to represent a spectrum of complexity, from low-dependency utilities (jsonpickle) to high-complexity image processing libraries involving C-extensions (Pillow). The selection criteria required repositories to have active maintenance,  $> 1k$  stars, and a history of well-documented issue resolution to serve as the ground truth. "Complexity" is qualitatively assessed based on dependency depth and code coupling (see Table 8.3). The evaluation utilized a curated set of  $N = 100$  coding tasks, split into 50 easy, 40 medium and 10 high-complexity challenges.

The evaluation focused on two aspects: the functional correctness of the proposed solution (checked manually) and pass/no-pass for all unit tests. A key principle of this methodology was to assess autonomous unsupervised problem resolution capabilities.

# 9 Ablation Studies

## 9.1 Components

We ablate (i) RL control (AIR w/o RL), and (ii) DTG (AIR w/o Graph).

Table 8.4: Public benchmarks for several top architectures.

%Resolved↑ on SWE-bench and pass rate↑ on APR benchmarks.

Baseline values are from the cited papers/sites; update to latest leaderboard snapshots.

Method	SWE-bench	Verified	SWE-bench Lite	HumanEvalFix
SWE-agent + Claude 3.5 Sonnet [11]	47.9	33.6	—	—
SWE-agent + Claude 4 Sonnet [11]	66.6 <sup>a</sup>	56.67	87.7 <sup>b</sup>	—
AutoCodeRover + GPT-4o [13]	46.2	37.3	—	—
OpenHands + Claude 3.5 Sonnet [12]	52.8	27.7	—	—
OpenHands + GPT-5 [12]	79.8	—	—	—
<b>AIR + Gemini 2.5 (Ours)</b>	<b>87.1</b>	<b>73.5</b>	—	—

<sup>a</sup> Reported %Resolved on SWE-bench at time of writing [31] (see the data from the original paper in [11]).

<sup>b</sup> HumanEvalFix pass@1 reported by SWE-agent [11]; included for completeness only.

For current SWE-bench leader-boards and variants (Full/Verified/Lite), see the website [31, 15].

Table 9.5: Ablations on SWE-bench Verified (%Resolved↑) and operations metrics.

Variant	%Resolved↑	MTTR (min)↓
AIR (full)	<b>87.1</b>	<b>8.9</b>
AIR w/o RL	82.5	1.5
AIR w/o Graph	56.2	4.6

## 10 Results and Analysis

### 10.1 Ablations: What matters and why

Table 9.5 shows that removing RL control (AIR w/o RL) reduces %Resolved from 87.1 to 82.5 while shrinking MTTR. In this case, the shorter MTTR reflects premature termination rather than efficient resolution: an agent gives up quicker without policy guidance.

Removing DTG (w/o GRAPH) yields a mid-range drop (%Resolved 56.2), indicating repository-scale context is a major contributor.

Overall, RL and GRAPH are the largest drivers of resolution rate.

### 10.2 Comparison with commercial tools

Based on the data provided, here are the calculated statistics for each model’s performance across the 10 projects (100 total issues). This test is less reliable than SWE-bench, because of several factors. First, we have a much lower number of datapoints. In particular, we pre-selected 10 issues (out of 100s for some repos) on the basis of their resolvability - we wanted to shortlist the purely coding issues that can be solved by just applying best coding practice and debugging skills. That introduces some biases.

The context for each case was built artificially, including all files that were referenced in final PR that solved the issue and which played the role of ground truth.

For evaluation we used a consistent and objective evaluation methodology. In particular, we awarded score +1 for solving the issue (all requirements in the ticket are satisfied) and all unit tests are passed. We did not penalize for time, cost or failed solutions. The Figure 10.4 depict the relative performance of each model, all data is aggregated in Table 10.6, with summary statistics in Table 10.7

Key Observations:

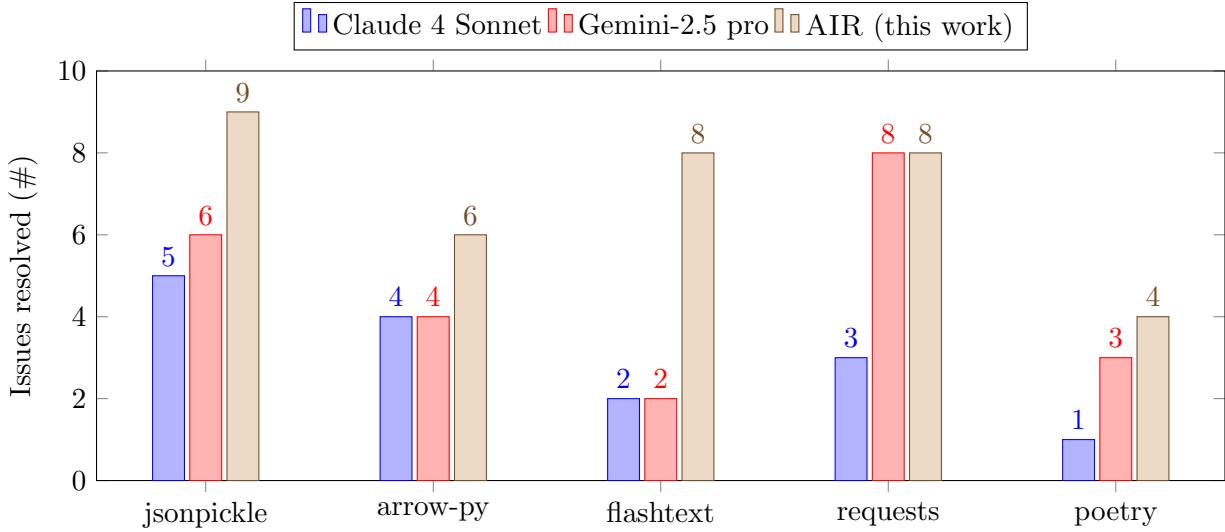


Figure 10.4: Testing results on GitHub Issues. Numbers indicate how many issues were resolved. We randomly selected 10 issues from each repository.

Table 10.6: Issue resolution on five OSS GitHub repos (10 issues each; same wall-clock + tool budget). Numbers indicate how many issues were resolved.

Project	AIR (this work)	Claude 4 Sonnet	Gemini-2.5 pro
jsonpickle	<b>9</b>	5	6
arrow-py	<b>6</b>	4	4
fashtext	<b>8</b>	2	2
requests	<b>8</b>	3	8
poetry	<b>4</b>	1	3
Pillow	<b>4</b>	0	0
python-qrcode	<b>8</b>	1	2
tinydb	5	<b>6</b>	6
urllib3	<b>9</b>	2	7
httpx	<b>9</b>	4	3

- AIR (this work) significantly outperformed the other models, solving 70% of all issues. It was the only model to solve at least 4 issues in every single project.
- Gemini-2.5 pro came in second with 41%, showing strong performance on specific libraries like requests (8/10) and urllib3 (7/10) but struggling with Pillow (0/10).
- Claude 4 Sonnet solved 28% of issues. It had a high variance, performing well on tinydb (6/10) but solving 2 or fewer issues in half of the projects.
- Difficulty: Pillow appeared to be the hardest project, with the two commercial models scoring 0 points and AIR scoring its minimum of 4 points. jsonpickle and requests generally saw higher success rates across the board.

Table 10.7: Performance statistics per model across 10 projects (100 total issues).

Statistic	AIR (This Work)	Claude 4 Sonnet	Gemini-2.5 pro
Total Solved	70	28	41
Success Rate	70.0%	28.0%	41.0%
Mean (per project)	7.0	2.8	4.1
Median	8.0	2.5	3.5
Std. Dev.	2.05	1.93	2.56
Min / Max	4 / 9	0 / 6	0 / 8

### 10.2.1 Performance Analysis and the "Semantic Gap"

The results in Figure 10.4 and Table 10.6 reveal a strong correlation between the explicitness of data flow and the agent’s success rate. AIR achieves a 70% resolution rate overall, showing particular strength in “loose-coupling” architectures like requests and urllib3 (8/10 and 9/10 respectively). In these repositories, logic errors are often distributed across multiple abstraction layers - a scenario where the DTG’s ability to trace data lineage allows the agent to “hop” over irrelevant middleware, a capability lacking in the file-based baselines.

### 10.2.2 Failure Case Study: The Pillow Repository

A notable deviation is observed in the Pillow repository, where commercial models scored 0/10 and AIR achieved only 4/10. We hypothesize this performance drop stems from the “Language Boundary” problem. Pillow relies heavily on C-extensions for image processing. The current DTG implementation parses Python ASTs but treats C-bindings as opaque edges. Consequently, when data flows into a compiled extension, the lineage is broken, blinding the agent. This limitation highlights the necessity for future work in cross-language graph construction to support hybrid-runtime environments.

## 11 Conclusion and Future Roadmap

We have argued that the dominant file-first, control-centric view of repositories is misaligned with both human debugging practice and the causal structure of many real bugs. By re-centering our representation around data states and transformations, the *Data-First Transformation Graph* (DTG) offers a compact and causally meaningful substrate for LLM-based repair agents.

Our empirical results on SWE-bench Verified, where AIR achieved an 87.1% resolution rate, validate that shifting from text-based retrieval to graph-based navigation substantially reduces the search complexity of logic repair. However, our analysis of failure cases, particularly within the Pillow repository, highlights critical avenues for future development. We outline three primary directions for the evolution of AIR:

**1. Breaking the Language Boundary (Polyglot DTGs):** Our experiments revealed that the current DTG construction, while effective for pure Python, struggles with hybrid runtimes (e.g., Python wrappers around C/C++ extensions). Future iterations must implement cross-language graph builders that can trace data lineage through Foreign Function Interfaces (FFI). This involves unifying AST parsers across languages into a shared intermediate representation, allowing the agent to “tunnel” through compiled extensions rather than treating them as opaque edges.

**2. Dynamic Graph Refinement via RL:** Currently, the DTG is static, constructed prior to the agent’s traversal. We propose a dynamic architecture where the agent can modifying the graph structure at runtime—collapsing well-tested subgraphs to save context or expanding ambiguous nodes for deeper inspection. By integrating this into the Reinforcement Learning policy, the agent can learn to optimize its own environment representation, effectively performing ”attention management” over the repository topology.

**3. Beyond Repair: Security and Refactoring:** The utility of the DTG extends beyond Automated Program Repair. We envision applying this data-centric view to automated security auditing, where ”taint analysis” becomes a native graph traversal task rather than a complex heuristic. Similarly, the DTG offers a robust foundation for architectural refactoring, allowing agents to identify and decouple ”god objects” based on data cohesion metrics rather than just line counts.

Transforming the LLM’s world model from a ”pile of files” to a navigable network of data flows, we move closer to truly autonomous systems capable of maintaining the invisible infrastructure of our digital civilization, precisely tuned to the inner logic of software. AIR represents the first step in this data-first transformation, bridging the gap between local code completion and systemic software reasoning.

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## A Building the DTG from source files

```
1     def _no_links_found_error(
2         self,
3         package: Package,
4         links_seen: int,
5         wheels_skipped: int,
6         sdists_skipped: int,
7         unsupported_wheels: set[str],
8     ) -> PoetryRuntimeError:
9         messages = []
10        info = (
11            f"This is likely not a Poetry issue.\n\n"
12            f" - {links_seen} candidate(s) were identified for the package\n"
13        )
14
15        messages.append(ConsoleMessage(info.strip()))
16
17        if unsupported_wheels:
18            messages += [
19                ConsoleMessage(
20                    "The following wheel(s) were skipped as the current project
environment does not support them "
21                    "due to abi compatibility issues.",
22                    debug=True,
23                ),
24                ConsoleMessage("\n".join(unsupported_wheels), debug=True)
25                    .indent(" - ")
26                    .wrap("warning"),
27                ConsoleMessage(
28                    "If you would like to see the supported tags in your project
environment, you can execute "
29                    "the following command:\n\n"
30                    "    <c1>poetry debug tags</>",
31                    debug=True,
32                ),
33            ]
34
35        source_hint = ""
36        if package.source_type and package.source_reference:
37            source_hint += f" ({package.source_reference})"
38
39        return PoetryRuntimeError(
40            reason=f"Unable to find installation candidates for {package}",
41            messages=messages,
42        )
```

Listing 1: A code snippet from poetry project (poetry/src/poetry/installation/chooser.py:125:197). Some non-essential lines were cut for brevity

The graph builder can extract the following raw constructs from this snippet of code (Table A.1), and eventually build a subgraph depicted in Figure A. We used a standard `ast` library for parsing python files, `neo4j` for storing nodes and edges, and `ChromaDB` as a vector storage tier for semantic search of relevant nodes/edges.

Construct Category	Count	Items identified
Function Definitions	1	_no_links_found_error
Arguments	6	self, package, links_seen, wheels_skipped, sdists_skipped, unsupported_wheels
Local Variable Assignments	3	messages, info, source_hint
Control Flow (Branches)	4	if statements
Return Statements	1	Returns PoetryRuntimeError
External/Global References	3	Package, PoetryRuntimeError, ConsoleMessage

Table A.1: Summary of extracted code constructs. We omit verbose metadata for brevity, such as file name, line number, type of variables, etc. All function arguments, function value and local variables will become the Data Nodes. Function name will become the basis for the edge. All formed structures will be stored in `neo4j` database, and the embeddings for underlying code will be stored in vector database (we use `ChromaDB`)

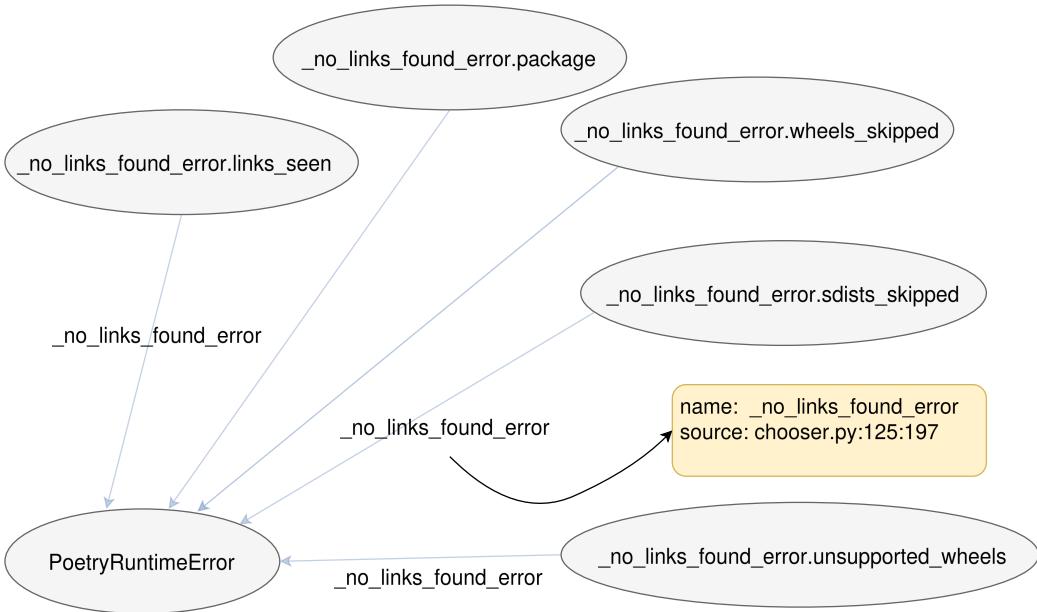


Figure A.1: The reconstructed sample of Data Transformation Graph given the raw data to build Nodes and Edges from Table A.1.

## B AI-assisted software tools

Table B.2 presents a comparison of market tier, interaction modality, and primary capabilities of today’s AI coding tools. While ”Professional” tier tools (e.g. Copilot, Cursor) dominate the interactive space via IDE integration, they operate primarily on a ”Human-in-the-Loop” synchronous model and hardly can be considered a serious AI technology. ”Specialized” agents (AlphaCode) excel at algorithmic synthesis but lack repository awareness. AIR is distinct in its focus on asynchronous, autonomous maintenance, targeting the ”Zero-Touch” quadrant currently unoccupied by major commercial providers.

Table B.2: The landscape of AI-assisted software tools (Q4’25). We distinguish market *tier*, *modality*, and *granularity* to expose differences that matter for maintenance automation.

<b>Product</b>	<b>Tier</b>	<b>Modality</b>	<b>Primary Capability</b>	<b>Notes / Differentiators (incl. SOTA area)</b>
GitHub Copilot [6]	Professional	IDE/Editor plugin	Predictive completion, chat, refactors	Strong ecosystem integration (PR comments, inline hints); SOTA for ergonomic code completion at scale.
Amazon CodeWhisperer [7]	Professional	IDE plugin	Completion + security hints	Security-aware suggestions; policy scanning baked into cloud workflows.
Tabmine [33]	Professional	IDE plugin	Local+cloud completion	Emphasis on on-device privacy modes; enterprise control.
Cursor [8]	Professional	AI-first IDE	Conversational edit, repo search	Editor tuned around agentic edits; tight repo context UX.
Claude Code [17]	Professional	Chat+tools	Conversational code reasoning	Long-context code reasoning; strong natural language guidance.
OpenAI Codex (legacy)	Professional	API/chat (retired)	Codegen foundation model	Historic baseline; catalyzed tool ecosystem.
Sourcegraph [34]	Professional	IDE plugin	Autonomous reasoning, comprehensive code editing	Advanced code assistant with many autonomous features
B44 (builder) [35]	Basic	Web builder	App scaffolding from prompts	Fast MVP creation; limited depth, human follow-through required.
Lovable [36]	Basic	Web builder	No/low-code + AI	Rapid prototyping; non-expert friendly; limited repo-scale change mgmt.
Replit (Ghost-writer) [37]	Basic	Web IDE	In-editor assist	Lightweight, education/startup focus; good DX, modest repo semantics.
AlphaCode family [27]	Specialized	Research system	Competition-style codegen	SOTA in competitive programming; not integrated with CI/CD or repos.
AlphaDev [26]	Specialized	Research system	Algorithm discovery/optim.	SOTA algorithm discovery; narrow domain, non-general maintenance.
Diffblue Cover	Specialized	JVM toolchain	Unit test synthesis	Industrial unit test generation; complements but does not fix issues.
Getafix/Infer lineage [25]	Specialized	Internal/OSS tools	Learned fix patterns + static analysis	Pattern mining for APR; depends on rich bug corpora; limited autonomy.
Factory.ai [38]	Specialized	Cloud integration	Agent-native Software development	Corporate level maintenance tool