AI Coding:
From Research to Millions of Developers

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"for pioneering the use of machine learning in
code assistance and program repair,
impacting millions of developers"

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Today's Journey

1. What is AI Coding?
2. Research Highlights
3. The Field Today and Tomorrow

Software is Eating the World

- Every modern system runs on code: aircraft, power grids, medical devices, financial markets, phones
- $\approx$ 30 million professional software developers worldwide (2024)
- Writing code is **hard, slow, and error-prone**
- A single bug can cost millions — or lives

The central tension

Demand for software grows faster than the supply of developers.

Can machines help write code?

What Does a Developer Actually Do?

1. **Understand** a problem or specification
2. **Write** code that solves it
3. **Test** whether the code is correct
4. **Debug** / **repair** when tests fail
5. **Maintain** and evolve code over years

AI Coding = automating or assisting any of these steps

Today we focus mostly on **writing** and **repairing** code.

The Key Insight: Code Is Language

Natural language (English):

```
The cat sat on the mat.
```

Programming language (Python):

```python
def greet(name):
    return "Hello, " + name
```

Fundamental observation (ca. 2009–2012)

Source code has **statistical regularities** just like natural language.

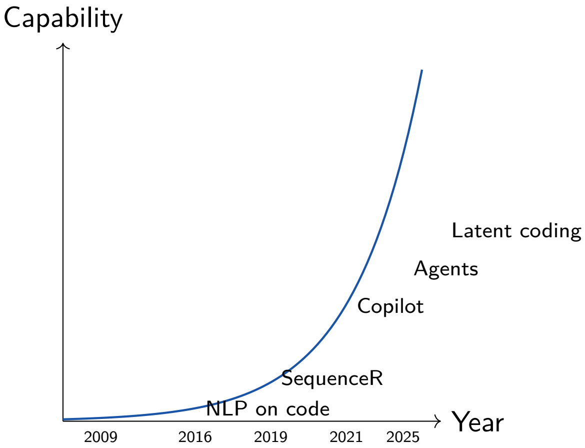
Sequences of tokens that appear often are likely to appear again — and can be *predicted*.

Hindle et al., *On the Naturalness of Software*, ICSE 2012 (Devanbu)

A Brief History of AI Coding (I)

- **1950s** First compilers: machines translate high-level text to machine code
- **1970s–90s** Syntax checkers, early static analysis
- **2009** **First training AI on code** (FSE 2009)
- **2012** *"On the Naturalness of Software"* — code modeled as language
- **2019** **Repairnator** — robot submits accepted patches to real projects; **SequenceR** — seq2seq end-to-end neural repair *(Monperrus et al.)*
- **2021** **GitHub Copilot** — LLMs for code completion, goes mainstream
- **2022** **Execution-based backpropagation** — test outcomes as training signal *(Ye, Martinez, Monperrus)*; neural repair of **security vulnerabilities** in C *(Chen, Kommrusch, Monperrus)*
- **2024–26** GPT, Claude, Gemini: conversational coding agents;

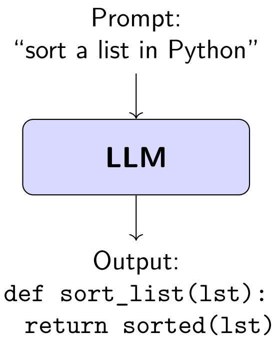
A Brief History of AI Coding (II): The Exponential



How Modern AI Coding Works — The Big Picture

Large Language Model (LLM)

- Trained on billions of lines of code + text
- Learns statistical patterns of tokens
- Given a *prompt*, predicts the next most likely tokens
- No explicit rules — emergent competence



Key point for engineers from other fields

This is **pattern completion at massive scale**—
the results are increasingly useful and sometimes remarkable.

Three Flavors of AI Coding

1. Code Completion

Developer types; AI continues.

Example: GitHub Copilot

Used by **millions daily**

2. Code Generation

Developer describes in English; AI writes code from scratch.

Example: ChatGPT, Claude

Changes **who can code**

3. Program Repair

AI finds a bug and fixes it automatically.

My research focus

Hardest problem — requires **understanding correctness**

*These three are converging into unified **AI coding agents**.*

Why Program Repair Is Hard

To fix a bug automatically, a system must:

1. Know what *correct behavior* looks like
2. Find the *location* of the fault
3. Generate a *valid patch*
4. Verify the patch *does not break anything else*

Each step is a research problem in itself.

The oracle problem

How do you know code is *correct*?

Test suites are the practical proxy: a patch passes if all tests pass.

But tests are incomplete — and this shapes everything.

My Research Arc (2009 – 2026)

- Open-source tools and datasets used worldwide

Paper #1 — Learning from Examples (FSE 2009)

"Learning from Examples to Improve Code Completion Systems"

ESEC/FSE 2009 — Bruch, Monperrus & Mezini

ACM SIGSOFT Impact Paper Award

Idea: Instead of syntactic completion rules, *learn* which API calls co-occur from a large corpus of existing programs.

- Mine usage patterns from thousands of open-source projects
- Rank completion suggestions by learned probability
- Works for any object-oriented API

Result

Dramatic improvement in completion accuracy over Eclipse's built-in completions on real Java APIs.

Foundational insight: code repositories are a goldmine of statistical knowledge about how code is written.

Paper #1 — Why It Started Everything

- **First paper** to show that *machine learning on large code corpora* directly improves developer tools
- Established the paradigm: **mine code** → **learn patterns** → **assist developers**
- Predates Hindle et al. (2012) and the "naturalness" wave — an independent but parallel insight
- Awarded the **ACM SIGSOFT Impact Paper Award**
- Every modern AI coding tool (Copilot, Cursor, . . .) is a scaled-up version of this core idea: learn from code history what comes next

Paper #2 — Repairnator (2019)

"Human-competitive Patches in Automatic Program Repair with Repairnator"

ICSE 2019 / Software Engineering in Practice

Idea: Build a software *robot* that:

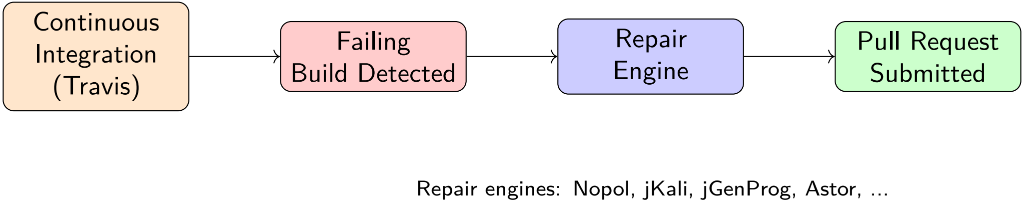
1. Monitors CI builds on GitHub continuously
2. Detects failing builds (= bugs caught by tests)
3. Applies automated repair techniques
4. Submits pull requests with patches

Result

Repairnator generated patches that were **accepted by human developers** in real open-source projects — indistinguishable from human patches.

First time ever.

Paper #2 — Repairnator: Architecture



- Ran 24/7 on 14,000+ real CI builds per month
- **Key insight:** automation enables *scale* — no human could monitor this
- Showed that repair is not just an academic exercise, shower human-competitiveness

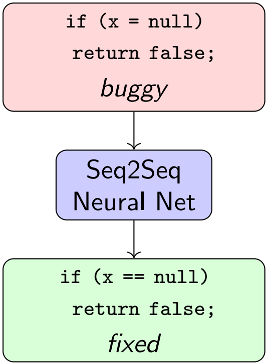
Paper #3 — SequenceR (2019)

“SequenceR: Sequence-to-Sequence Learning for End-to-End Program Repair”

IEEE Transactions on Software Engineering, 2019
(Chen, Kommrusch, Tufano, Pouchet, Poshyvanyk, Monperrus)

Idea: Treat bug repair as a *translation* task.

- Input: buggy code line
- Output: fixed code line
- Model: sequence-to-sequence (encoder-decoder) neural network, trained on thousands of past bug fixes



Paper #3 — SequenceR: Why It Matters

- **First** end-to-end neural network for program repair
- Introduced the idea of *copy mechanism*: the model can copy tokens from the surrounding context (crucial for code), still today in coding agents
- No hand-crafted rules — **learned entirely from data**
- Published in IEEE TSE 2019 — one of the most-cited works in neural repair

What changed

Before SequenceR: repair needed hand-coded templates and domain knowledge.
After SequenceR: a neural model trained on commit history could repair code.
This was the **transition point** to modern AI-driven program repair.

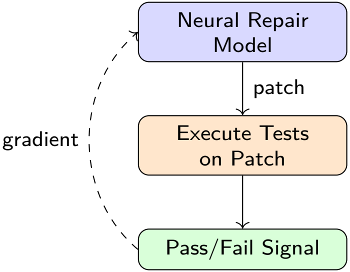
Paper #4 — Neural Repair with Execution (ICSE 2022)

"Neural Program Repair with Execution-based Backpropagation"

ICSE 2022 — He Ye, Matias Martinez, Martin Monperrus

Problem: Previous neural repair models are trained only on *syntactic* correctness (does it look like a a patch?).

Idea: Train the model using *test execution feedback* — run the patch, see if tests pass, backpropagate that signal.



Paper #4 — Why Execution Feedback Is a Breakthrough

- The model learns that *semantic correctness* (tests passing) is the goal, not just syntactic plausibility
- Bridges the gap between **statistical language models** and **program semantics**
- Analogous to reinforcement learning from human feedback (RLHF) — but the "human feedback" is replaced by **automated test execution**
- Significant improvement on Defects4J benchmark

Broader significance

This paper laid groundwork for using automated oracles (tests, compilers, formal verifiers) as training signals — a paradigm now central to the latest code LLMs and coding agents.

Paper #5 — Security Vulnerability Repair (TSE 2022)

"Neural Transfer Learning for Repairing Security Vulnerabilities in C Code"

IEEE Transactions on Software Engineering, 2022
(Chen, Kommrusch, Monperrus)

IEEE TSE Best Paper Award

Motivation: Security vulnerabilities (buffer overflows,
SQL injections, ...) are catastrophic. Manual patching is slow.

Idea: Transfer a model trained on general bug fixes to the domain of *security vulnerabilities* in C.

Impact

- Demonstrated that neural repair generalizes across domains
- Security patching is a billion-dollar problem — automation matters
- Used CVE datasets for evaluation

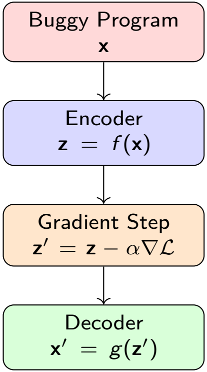
Paper #6 — Gradient-Based Program Repair

"Repairing Programs Directly in Continuous Latent Space"

Most futuristic direction, current research in my group

Key idea: Instead of generating a patch token-by-token, *differentiate through the program representation* directly.

- Encode the buggy program into a continuous vector
- Use gradient descent to move the vector toward a correct program
- Decode back into source code
- No discrete search — fully differentiable pipeline



Paper #6 — Why Gradient-Based Repair Matters

- **Escapes the combinatorial explosion** of discrete patch search: gradient descent is orders of magnitude more directed
- **Unified training signal**: the correctness loss (test pass/fail) flows directly back in the vector space
- **Connects program repair to the topology of code embeddings**: bugs are points in latent space; fixes are nearby, reachable by gradient steps
- Opens the door to **simultaneous multi-location repair** as a single optimisation problem

Long-term vision

If programs can be continuously optimised like neural network weights, the boundary between *training a model* and *repairing software* dissolves, a fundamental shift in how we think about correctness.

Common Thread Across Papers

Paper	**Key Contribution**	**Legacy**
Learning from Ex. (FSE'09)	ML on code corpora	Copilot paradigm
Repairnator (2019)	Repair at CI scale	Industrial deployment
SequenceR (2019)	End-to-end neural repair	Coding agent
Exec. BP (2022)	Semantic training signal	Post-training RL
Security (TSE'22)	Transfer to security	Practical impact
Gradient repair	Differentiable repair	Future paradigm

Each paper pushed one boundary; together they define a research program.

What AI Coding Tools Can Do Today

Impressive successes:

- Repair: Fix **complex, multi-file bugs** spanning thousands of lines
- **Write entire programs and almost systems** from a natural-language description
- Complete features end-to-end: spec → code → tests → docs
- Translate and modernize legacy codebases (COBOL, Fortran)
- Solve competitive programming problems (Olympiad level)
- Pass senior-level coding interviews

Persistent limitations:

- Hallucinate non-existent APIs
- Miss subtle semantic and concurrency errors
- Cannot reliably verify own output
- Poor at long-horizon architectural integrity
- Security vulnerabilities introduced silently

Open Research Problems I Find Most Exciting

1. **Test-time compute for repair**
   Let the model "think longer" on hard bugs — analogous to AlphaGo's MCTS
2. **Learning from execution at scale**
   Use compilers, fuzzers, formal verifiers and tests as infinite training signal
3. **Latent-space program synthesis**
   Operate directly in embedding space, not token-by-token — potentially orders of magnitude faster
4. **ARC-AGI and beyond**
   Program synthesis as a path to general intelligence

The Human-AI Collaboration Question

Not replacement — augmentation

- Developers using Copilot are -20%, 100% faster on benchmark tasks
- But: code review load *increases* — more code to read
- Skills that become more valuable: system design, requirements, verification
- Skills that become less valuable: boilerplate, syntax memorization

Key problems

Reliability?
Liability?
Economics?

Reflections: What I Got Right and Wrong

Predictions that held:

- Code *is* a language (most) amenable to ML
- Neural approaches *would* dominate repair
- Execution feedback *is* crucial for training
- Scale matters — big models beat clever heuristics

What I underestimated:

- **Speed** of LLM capability jumps
- **Breadth**: LLMs generalize across dozens of programming languages with no fine-tuning
- **Adoption**: millions of users in months, not years
- **Societal impact**: education, workforce — all disrupted simultaneously

For Engineers from Other Fields: The Takeaway

AI Coding idemonstrably works at scale

- Code is *formal* enough that correctness is verifiable (unlike text or images)
- Code has *abundant training data* (billions of lines on GitHub)
- The feedback loop is *fast and cheap* (just run the tests)

This makes AI coding a *leading indicator*:
the techniques developed here — neural search, execution-based training, iterative agentic loops — are being applied to:

- Mathematical proof
- Hardware, chip design (VHDL, SystemVerilog, Google's AlphaChip)
- AI for science

Summary

1. **AI Coding** = using machine learning to write and maintain code
2. The key insight: **code is the most learnable language** — statistical regularities and clear semantics enable prediction
3. My research arc: from code completion (2009)
   to SequenceR's neural repair (2019) to execution-driven training (2022)
   to large-language models (2023)
4. **Today**: millions of developers use AI daily; entire startups built on this
5. **Tomorrow**: agentic systems that verify their own output, learn from execution, and eventually produce reliable systems.

Acknowledgments

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The open-source community —
without whom none of this is possible.

A personal note

When I started working on
automated program repair in 2011,
it was considered an impossible curiosity.

It has become a multi-billion $ industry.

Thank you

AI Coding: From Research to Millions of Developers

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`https://www.monperrus.net/martin/publications`

Papers, datasets, and tools: all open-source.
The living review on program repair is continuously updated at
`monperrus.net/martin/repair-living-review`

Slides made with LaTeX Beamer.