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[...]

## 1.1 Typed functional programming as a foundation for ML models

**Problem 1.1.1.** Systems like *OpenAI Codex* [CTJ<sup>+</sup>21], and *CodeT5* [WWJH21, LWG<sup>+</sup>22, WLK<sup>+</sup>23], and *AlphaCode* [LCC<sup>+</sup>22] generate code as plain text. This leads to (i) syntactically valid but semantically broken code, (ii) type errors, and (iii) violations of safety constraints.

**Possible solution:** A typed lambda calculus foundation provides rich static guarantees, via *purity, types, resource constraints, better priors for code generation, type-directed completion*.

## 1.2 Typed Code Models

Models trained on type annotations (e.g., Haskell, OCaml, Rust) can perform type-aware generation.

## 1.3 Neural Program Synthesis with Types

e.g., DeepCoder and successors use type information as features to guide synthesis.

## 1.4 Monads and Effect Systems in ML Safety

a. Monads as Models of Effects Monads are widely used in Haskell to isolate side effects (IO, randomness, state), and to model pipelines.

ML models, especially in reinforcement learning and simulation, deal with effects (e.g., randomness, stateful environments). Using monadic abstractions could:

- make dataflow pipelines compositional and safe,
- allow reasoning about effects (e.g., logging, uncertainty),
- embed constraints in types (e.g., a function that only accesses a read-only dataset).

This is one of the core ideas in:

Probabilistic Programming Languages (PPLs) like Hakaru, Anglican, and Pyro, where the probabilistic model is itself a monadic computation.

Effect systems in ML IRs, such as Google’s Relay (part of TVM), which tracks purity/effects.

## 1.5 Category Theory and Differentiable Programming

Category theory underpins both monads and many concepts in automatic differentiation and differentiable programming.

Projects like:

DiffSharp (F#-based autodiff using category theory),

JAX and Haskell’s backprop, and

Conal Elliott’s work on denotational AD using categories,

explore categorical formulations of AD as functorial transformations, leading to better compositionality and correctness.

## 1.6 Safe ML via Typed DSLs

Inspired by Haskell MLIR (Multi-Level IR) and TVM’s Relay explore typed, functional-style IRs for safe optimization and compilation.

TensorFlow Eager and JAX both adopt a functional, pure style to enable more robust transformations (e.g., JIT, vectorization).

Haskell-based DSLs like Grenade, TorchHask, and DeepLearningHaskell offer ways to build ML pipelines with compile-time guarantees.

## 1.7 Practical ML Projects Using Haskell

Although niche, some serious Haskell ML libraries exist:

Hasktorch: Haskell bindings to LibTorch with typed tensors and differentiable programming.

Grenade: A fully Haskell-native DL framework with type-safe layer composition.

Edward Kmett’s category-theoretic autodiff experiments.

These show how GADT-based types, dependent typing, and monads can be used to enforce shape, operation safety, and effect constraints in ML pipelines.

## 1.8 S

Summary: Why This is Gaining Traction The motivation is this:

Modern ML models are too brittle, opaque, and unrestricted. Haskell-like systems offer tools (types, purity, monads, category theory) to impose structure, improve interpretability, and enable safer code synthesis and reasoning.

This isn’t just academic—industry is gradually adopting functional and type-theoretic ideas into production pipelines, even if not full Haskell.

Would you like a deeper dive into any of these (e.g., how monads model probabilistic computations, or how types guide neural program synthesis)?

## References

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