The Future of Programming Languages

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Thesis:
The future of performance optimization is better programming models, not better optimizers.
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Hypothesis:

To build better programming models for people, we need better models of people programming.
Importance of cognition is well-known

The large number of people engaged in this work, as well as the complexity of the task itself should make programming behavior of considerable interest to cognitive psychology. Indeed, though significant quantities of programmers have been available for only the past 10 years, researchers have been quick to turn their attention to cognitive aspects of programming, and a small, but growing body of studies now exists. As Ruven Brooks. “Towards a theory of the cognitive processes in computer programming.” 1977

It is also the case that learning to program is going to be an increasingly important goal in our society. Thus, understanding its acquisition will have enormous educational impact. The issue of training novel, complex, and technical skills is a major one for our “high-tech” society with its need to retrain a large fraction of the work force. This retraining will not always be in programming, but in studying programming we are addressing issues important to many technical skills.

John Anderson et al. “Learning to Program in LISP.” 1984
Programmers Are Users Too: Human-Centered Methods for Improving Programming Tools

Brad A. Myers, Carnegie Mellon University
Andrew J. Ko, University of Washington
Thomas D. LaToza, George Mason University
YoungSeok Yoon, Google
Existing work is hard to generalize

Of the controlled experiments, only three show an effect large enough to have any practical significance. … Unfortunately, they all have issues that make it hard to draw a really strong conclusion.

In the Prechelt study, the populations were different between dynamic and typed languages, and the conditions for the tasks were also different. There was a follow-up study that … literally involves comparing code from Peter Norvig to code from random college students.
Hypothesis:
Two main paths forward: large-scale analysis, and more rigorous cognitive science.
Survey says: PL features matter least

Figure 5: Importance of different factors when picking a language. Self-reported for every respondent's last project. Bars show standard error. E = Extrinsic factor, I = Intrinsic, M = Mixed. Shows results broken down by company size for respondents describing a work project and who indicated company size. (Slashdot, n = 1679)
Survey says: Java is as hard as JS

Figure 7: Median reported speed of language acquisition.
Bars are standard error. (Slashdot, n = 1679)
Deep knowledge tracing at scale

In this paper, we contribute an approach to promoting metacognitive awareness in introductory programming settings and investigate its effects on help requests, productivity, self-efficacy, and growth mindset.

Programming is not merely about language syntax and semantics, but more fundamentally about the iterative process of refining mental representations of computational problems and solutions and expressing those representations as code.

Subvocalization for tracking cognition

Figure 3. EMG and Programming events over 13 minutes of activity.

Chris Parnin. “Subvocalization – Towards Hearing the Inner Thoughts of Developers”. 2011
Programming is … about the iterative process of refining mental representations of computational problems and solutions and expressing those representations as code.

Programmers accumulate knowledge about their programs over time

• Programming a new system is touch-and-go
  - Don’t know what the types should be, data schemas rapidly evolved
  - Code may be partially broken, but those paths won’t be tested
  - “Almost right” is better than a compiler error

• Once you are more confident with types, write them down
  - And have the compiler enforce them

• Once you hit a bottleneck, add performant code
  - Manage memory yourself, don’t rely on the garbage collector
Taxonomy of modern GPPLs

More types

Fewer types

Automatic memory management

Manual memory management

Lua
JavaScript

Ruby
Python

Go
Java
C#
OCaml
Swift

C
C++
Rust

Assembly languages

Scripting languages

WASM

“Systems” languages

x86

LLVM

??? languages
Fibonacci: Lua

```lua
function fib(n)
    if n == 0 or n == 1 then
        return n
    else
        return fib(n - 1) + fib(n - 2)
    end
end
```
let rec fib (n : any) : any =
  let n : int = Obj.magic n in
  if n = 0 || n = 1 then
    n
  else
    Obj.magic (fib (Obj.magic (n - 1))) +
    Obj.magic (fib (Obj.magic (n - 2)))
Fibonacci: Rust

```rust
defib(n_dyn: Rc<Any>) -> Rc<Any> {
    let n_static: &i32 =
        n_dyn.downcast_ref::<i32>().unwrap();
    if *n_static == 0 {
        Rc::new(Box::new(*n_static))
    } else {
        let n1 = fib(Rc::new(Box::new(n_static - 1)));
        let n2 = fib(Rc::new(Box::new(n_static - 2)));
        Rc::new(
            n1.downcast_ref::<i32>().unwrap() +
            n2.downcast_ref::<i32>().unwrap())
    }
}
```
Key difference is static analysis

• What distinguishes languages is the level of static analysis
  - Plus facilities for checking non-inferrable/annotatable info at runtime
  - Tier 1 (“scripting”): runtime types and memory
  - Tier 2 (“functional”): static types, runtime memory
  - Tier 3 (“systems”): static types and memory

• It’s “easy” to defer static checks to runtime, but conceptual/syntactic overhead increases
  - Rc<T> and Any in Rust
  - Obj.magic in OCaml
We need solutions to permit gradual migration from one to the other
Gradual typing crosses the type barrier

```javascript
function greeter(person: string) {
  return "Hello, " + person;
}

let user = [0, 1, 2];

document.body.innerHTML = greeter(user);
```

Re-compiling, you’ll now see an error:

```
error TS2345: Argument of type 'number[]' is not assignable to parameter of type 'string'.
```

---

From Python...

```python
def fib(n):
    a, b = 0, 1
    while a < n:
        yield a
        a, b = b, a+b
```

...to statically typed Python

```python
def fib(n: int) -> Iterator[int]:
    a, b = 0, 1
    while a < n:
        yield a
        a, b = b, a+b
```
Gradual memory management?

- No easy way to mix memory management solutions
  - C++/Rust make it possible to mix reference counting and lifetimes
  - But with heavy syntactic overhead

- Lua virtual stack solved this problem, but not easily

- Little/no published research here—open problem!
Issues in gradual systems

• **Debuggability and blame**
  - How do we know whether a value has had its type inferred or deferred? (Likely need to investigate IDE integration)
  - If an error occurs, what’s the source of the cause? (Who’s to blame?)
  - Broadly: when the compiler makes a decision for us, we need to understand that decision

• **Performance**
  - “Is Sound Gradual Typing Dead?” - 0.5x - 68x overhead relative to untyped code
  - No existing systems take advantage of potential perf benefits
Takeaways

- Understand the human to build better programming models

- Gradual programming is a promising PL technique that matches the human programming process