# Ace: Growing a Statically-Typed Language Inside a Python


## Abstract

Evidence suggests that programmers are reluctant to adopt new programming languages to gain access to new abstractions, even when they agree that these abstractions would be valuable to them. This suggests a need for languages that are *compatible* with existing languages, tools and infrastructure and *internally extensible*, so that adopting a new primitive abstraction requires only importing a library in the usual way.

In this paper, we introduce Ace, a language compatible with tools and infrastructure developed for Python, one of the most widely-adopted dynamically-typed languages today. While Python, like other similar languages, was designed for simple scripting tasks, Ace is designed for more complex situations where static typechecking and programmatic control over compilation may be beneficial. Unlike most statically-typed languages, however, Ace's type system and semantics can be extended from within by novel mechanisms that avoid key interference issues faced by previous mechanisms. We show that these can be used to implement a range of statically-typed functional, object-oriented, parallel, low-level and domain-specific abstractions, as well as safe interoperability layers with existing languages, as orthogonal libraries.


## 1. Introduction

Asking programmers to import a new library is far more practical than asking them to adopt a new programming language. Indeed, recent empirical studies underscore the difficulties of driving new languages into adoption, finding that extrinsic factors like compatibility with existing codebases and libraries, team familiarity and tool support are at least as important as intrinsic factors [10, 24, 25]. As a result, many developers cannot use abstractions they might prefer because these abstractions are only available in languages they cannot adopt [23, 24]. This issue was perhaps most succinctly expressed by a participant in a recent study by Basili et al. [2] who stated "I hate MPI, I hate C++. [But] if I had to choose again, I would probably choose the same."

Unfortunately, researchers and domain experts who design and develop potentially useful new abstractions can find it difficult to implement them in terms of the general-purpose abstraction mechanisms available in mainstream languages. This is particularly salient for abstractions that require support from the typechecker or compiler, such as those focused on correctness and performance, as well as those that introduce more concise or natural notations for existing abstractions. For example, a recent controlled study comparing a new language, Habanero-Java (HJ), with a comparable library, `java.util.concurrent`, found that the language-based approach was more concise, correct and easy-to-use, but concluded that the library-based approach was more practical outside the classroom because HJ introduced new constructs and keywords into Java, requiring the adoption of a new toolchain, which could lead to compatibility issues with plain Java code [7].

Internally-extensible languages promise to reduce the need for new standalone languages by giving abstraction providers more direct control over a base language's syntax and semantics from within libraries. By using such a language, programmers gain the ability to granularly import the primitive abstractions best suited to each part of their application or library. The research community thus gains the ability to more easily develop, deploy and evaluate new abstractions in the context of existing codebases, narrowing one of the gaps between research and practice [2].

Unfortunately, internally-extensible languages available today have several problems. First, an extension mechanism itself may require modifying a base language with constructs for defining, importing and using extensions. The extension mechanism is not itself a library, so it faces a "bootstrapping" problem: it must overcome many of the same extrinsic issues as other new languages like HJ. The extension mechanisms available today also have some intrinsic problems related to safety and expressiveness that require technical solutions before it would be appropriate to widely rely on them.

This paper describes the design and implementation of Ace, an internally-extensible language designed considering both extrinsic and intrinsic criteria. To solve the bootstrapping problem, Ace is implemented entirely as a library within the popular Python programming language. Ace and Python share a common syntax and package system, allowing Ace to leverage its well-established tools and infrastructure directly. Python serves as the compile-time metalanguage for Ace, but Ace functions themselves do not operate according to Python's fixed dynamically-typed semantics (cf. [1, 27]). Instead, Ace has a statically-typed semantics that can be extended by users from within libraries.

More specifically, each Ace function can be annotated with a base semantics that determines the meaning of simple expressions like literals and certain statements. The semantics of the remaining expressions and statements are governed by logic associated with the type of a designated subexpression. We call the user-defined base semantics *active bases* and the types in Ace *active types*, borrowing terminology from *active libraries* ([34], see Sec. 5). Both are objects that can be defined and manipulated at compile-time using Python. An important consequence of this mechanism is that it permits *compositional* reasoning – active bases and active types govern only specific non-overlapping portions of a program. As a result, clients are able to import any combination of extensions with the confidence that link-time ambiguities cannot occur (unlike many previous approaches, as we discuss in Sec. 5).

The *target* of compilation is also user-defined. We will show examples of Ace targeting Python as well as OpenCL and CUDA,

lower-level languages often used to program graphics hardware. An active base or type can support multiple *active targets*, which mediate translation of Ace code to code in a target language. Ace functions targeting a language with Python bindings can be called directly from Python scripts, with compilation occurring implicitly. For some data structures, types can propagate from Python into Ace. We show how this can be used to streamline the kinds of interactive workflows that Python is often used for. Ace can also be used non-interactively from the shell, producing source files that can be further compiled and executed by external means.

The remainder of the paper is organized as follows: in Sec. 2, we describe the basic structure and usage of Ace with an example library that internalizes and extends the OpenCL language. Then in Sec. 3, we show how this and other libraries are implemented by detailing the extension mechanisms within Ace. To explain and demonstrate the expressiveness of these mechanisms (in particular, active types) further, we continue in Sec. 4 by showing a diverse collection of abstractions drawn from different language paradigms that can be implemented as orthogonal libraries in Ace. We include functional datatypes, objects, and several other abstractions. In Sec. 5, we compare Ace to related work on language extensibility and metaprogramming. We conclude in Sec. 6 by summarizing our contributions, discussing the essential features needed by a host language to support these mechanisms, and describing their limitations and potential future work.

## 2. Language Design and Usage

Listing 1 shows an example of an Ace file. As promised, the top level of an Ace file is written directly in Python, requiring no modifications to the language (versions 2.6+ or 3.3+) nor features specific to CPython (so Ace supports alternative implementations like Jython and IronPython). This choice pays immediate dividends on line 1: Ace's package system is Python's package system, so Python's build tools (e.g. `pip`) and package repostories (e.g. `PyPI`) are directly available for distributing Ace libraries.

The top-level statements in an Ace file, like the `print` statement on line 10, are executed to control the compile-time behavior, rather than the run-time behavior, of the program. That is, Python serves as the *compile-time metalanguage* (and, as we will see shortly, the *type-level language*) of Ace. Functions containing run-time behavior, like `map`, are governed by a semantics that can differ from Python's (in ways that we will describe below), but they share Python's syntax. As a consequence, users of Ace immediately benefit from an ecosystem of well-developed tools that work with Python syntax, including parsers, code highlighters, editor modes, style checkers and documentation generators.

### 2.1 OpenCL as an Active Library

The code in this section uses `clx`, an example library implementing the semantics of the OpenCL programming language and extending it with some additional useful types, which we will discuss shortly. Ace itself has no built-in support for OpenCL.

To briefly review, OpenCL provides a data-parallel SPMD programming model where developers define functions, called *kernels*, for execution on *compute devices* like GPUs or multi-core CPUs [14]. Each thread executes the same kernel but has access to a unique index, called its *global ID*. Kernel code is written in a variant of C99 extended with some new primitive types and operators, which we will introduce as needed in our examples below.

### 2.2 Generic Functions

Lines 3-4 introduce `map`, an Ace function of three arguments that is governed by the *active base* referred to by `clx.base` and targeting the *active target* referred to by `clx.opencl`. The active target

**Listing 1** [`listing1.py`] A generic data-parallel higher-order map function targeting OpenCL.

```
1  import ace, examples.clx as clx
2
3  @ace.fn(clx.base, clx.opencl)
4  def map(input, output, f):
5      thread_idx = get_global_id()
6      output[thread_idx] = f(input[thread_idx])
7      if thread_idx == 0:
8          printf("Hello, run-time world!")
9
10 print "Hello, compile-time world!"
```

**Listing 2** [`listing2.py`] Metaprogramming with Ace, showing how to construct generic functions from abstract syntax trees.

```
1  import ace, examples.clx as clx, ast, astx
2
3  _fn = ace.fn(clx.base, clx.opencl)
4
5  scale = _fn(ast.parse("""def scale(x, s):
6      return x * s"""))
7
8  negate = _fn(astx.specialize(scale.ast, "negate",
9      s=ast.parse("-1")))
```

determines which language the function will compile to (here, the OpenCL kernel language) and mediates code generation.

The body of this function, highlighted in grey for emphasis, does not have Python's semantics. Instead, it will be governed by the active base together with the active types used within it. No such types have been provided explicitly, however. Because our type system is extensible, the code inside could be meaningful for many different assignments of types to the arguments. We call functions awaiting types *generic functions*. Once types have been assigned, they are called *concrete functions*.

Generic functions are represented at compile-time as instances of `ace.GenericFn` and consist of an abstract syntax tree, an active base and an active target. The purpose of the *decorator* on line 3 is to replace the Python function on lines 4-8 with an Ace generic function having the same syntax tree and the provided active base and active target. Decorators in Python are simply syntactic sugar for applying the decorator function directly to the function being decorated [1]. In other words, line 3 could be replaced by inserting the following statement on line 9:

```
map = ace.fn(clx.base, clx.opencl)(map)
```

The abstract syntax tree for `map` is extracted using the Python standard library packages `inspect` (to retrieve its source code) and `ast` (to parse it into a syntax tree).

### 2.3 Metaprogramming in Ace

Generic functions can be generated directly from ASTs as well, providing Ace with support for straightforward metaprogramming. Listing 2 shows how to generate two more generic functions, `scale` and `negate`. The latter is derived from the former by using a library for manipulating Python syntax trees, `astx`. In particular, the `specialize` function replaces uses of the second argument of `scale` with the literal `-1` (and changes the function's name), leaving a function of one argument.

### 2.4 Concrete Functions and Explicit Compilation

To compile a generic function to a particular *concrete function*, a type must be provided for each argument, and typechecking and translation must then succeed. Listing 3 shows how to explicitly provide type assignments to `map` using the subscript operator (implemented using Python's operator overloading mechanism). We

**Listing 3** [listing3.py] The generic map function compiled to map the negate function over two types of input.

```
1  import listing1, listing2, ace, examples.clx as clx
2
3  T1 = clx.Ptr(clx.global_, clx.float)
4  T2 = clx.Ptr(clx.global_, clx.Cplx(clx.int))
5  TF = listing2.negate.ace_type
6
7  try: map_neg_f32 = listing1.map[[TF, T1, T1]]
8  except ace.TypeError as e: print e.full_msg
9  map_neg_f32 = listing1.map[[T1, T1, TF]]
10 map_neg_ci32 = listing1.map[[T2, T2, TF]]
```

**Listing 4** Compiling listing3.py using the acec compiler.

```
1  $ acec listing3.py
2  Hello, compile-time world!
3  [ace] TypeError in listing1.py (line 6, col 28):
4        'GenericFnType(negate)' does not support [].
5  [acec] listing3.cl successfully generated.
```

attempt to do so three times in Listing 3. The first, on line 3.7, fails due to a type error, which we handle so that the script can proceed. The error occurred because the ordering of the argument types was incorrect. We provide a valid ordering on line 3.9 to generate the concrete function map_neg_f32. We then provide a different type assignment to generate the concrete function map_neg_ci32. Concrete functions are instances of ace.ConcreteFn, consisting of an abstract syntax tree annotated with types and translations along with a reference to the original generic function.

To produce an output file from an Ace "compilation script" like listing3.py, the command acec can be invoked from the shell, as shown in Listing 4. The acec compiler (a simple Python script) operates in two stages:

1. Executes the provided Python file (listing3.py).
2. Extracts the translations from concrete functions and other top-level constructs (e.g. types requiring declarations, or generated imports and pragmas) in the top-level Python environment. This may produce one or more files as mediated by the active targets that were used (here, just listing3.cl, but a web framework built upon Ace might produce separate HTML, CSS and JavaScript files; see Sec. 3.3).

In this case, stage 1 results in the output on lines 4.2-4.4. The type error printed on lines 4.3-4.4 will be explained in the next section. The compiler then enters stage 2 and concludes with the message on line 4.5 to indicate that one file was generated. This file is shown in Listing 5 and can be used by any programs that consume OpenCL code (e.g. a C program that invokes the generated kernels via the OpenCL host API). We will show in Section 2.6 that for targets with Python bindings, such as OpenCL, CUDA, C, Java or Python itself, generic functions can be executed directly, without any of the explicit compilation steps in Listings 3-4.

### 2.5 Types

Lines 3.3-3.5 construct the types assigned to the arguments of map on lines 3.7-3.10. In Ace, types are themselves values that can be manipulated at compile-time. This stands in contrast to other contemporary languages, where user-defined types (e.g. datatypes, classes, structs) are written declaratively at compile-time but cannot be constructed, inspected or passed around programmatically. More specifically, types are instances of a Python class that implements the ace.ActiveType interface (see Sec. 3.1). As Python values, types can be assigned to variables when convenient (removing the need for facilities like typedef in C or type in Haskell). Types,

**Listing 5** [listing3.cl] The OpenCL file generated by Listing 4.

```
1  float negate__0_(float x) {
2    return x * -1;
3  }
4
5  kernel void map_neg_f32(global float* input,
6      global float* output) {
7    size_t thread_idx = get_global_id(0);
8    output[thread_idx] = negate__0_(input[thread_idx]);
9    if (thread_idx == 0) {
10     printf("Hello, run-time world!");
11   }
12 }
13
14 int2 negate__1_(int2 x) {
15   return (int2)(x.s0 * -1, x.s1);
16 }
17
18 kernel void map_neg_ci32(global int2* input,
19     global int2* output) {
20   size_t thread_idx = get_global_id(0);
21   output[thread_idx] = negate__1_(input[thread_idx]);
22   if (thread_idx == 0) {
23     printf("Hello, run-time world!");
24   }
25 }
```

like all compile-time objects derived from Ace base classes, do not have visible state and operate in a referentially transparent manner (by constructor memoization, which we do not detail here).

The type named T1 on line 3.3 corresponds to the OpenCL type global float*: a pointer to a 32-bit floating point number stored in the compute device's global memory (one of four address spaces defined by OpenCL [14]). It is constructed by applying clx.Ptr, which is an Ace type constructor corresponding to pointer types, to a value representing the address space, clx.global_, and the type being pointed to. That type, clx.float, is in turn the Ace type corresponding to float in OpenCL (which, unlike C99, is always 32 bits). The clx library contains a full implementation of the OpenCL type system (including behaviors, like promotions, inherited from C99). Ace is *unopinionated* about issues like memory safety and the wisdom of such promotions. We will discuss how to implement, as libraries, abstractions that are higher-level than raw pointers in Sec. 4, but Ace does not prevent users from choosing a low level of abstraction or "interesting" semantics if the need arises (e.g. for compatibility with existing libraries; see the discussion in Sec. 6). We also note that we are being more verbose than necessary for the sake of pedagogy. The clx library includes more concise shorthand for OpenCL's types: T1 is equal to clx.gp(clx.f32).

The type T2 on line 3.4 is a pointer to a *complex integer* in global memory. It does not correspond direrctly to a type in OpenCL, because OpenCL does not include primitive support for complex numbers. Instead, it uses an active type constructor clx.Cplx, which includes the necessary logic for typechecking operations on complex numbers and translating them to OpenCL (Sec. 3.1). This constructor is parameterized by the numeric type that should be used for the real and imaginary parts, here clx.int, which corresponds to 32-bit OpenCL integers. Arithmetic operations with other complex numbers, as well as with plain numeric types (treated as if their imaginary part was zero), are supported. When targeting OpenCL, Ace expressions assigned type clx.Cplx(clx.int) are compiled to OpenCL expressions of type int2, a *vector type* of two 32-bit integers (a type that itself is not inherited from C99). This can be observed in several places on lines 5.14-5.21. This choice is merely an implementation detail that can be kept private to clx, however. An Ace value of type clx.int2 (that is, an actual OpenCL vector) *cannot* be used when a clx.Cplx(clx.int) is

expected (and attempting to do so will result in a static type error). `clx.Cplx` truly extends the type system, it is not a type alias.

The type `TF` on line 3.5 is extracted from the generic function `negate` constructed in Listing 2. Generic functions, according to Sec. 2.2, have not yet had a type assigned to them, so it may seem perplexing that we are nevertheless extracting a type from it. Although a conventional arrow type cannot be assigned to `negate`, we can give it a *singleton type*: a type that simply means "this expression is the *particular* generic function `negate`". This type could also have been explicitly written as `ace.GenericFnType(listing2.negate)`. During typechecking and translation of `map_neg_f32` and `map_neg_ci32`, the call to `f` on line 1.6 operates by using the types of the provided arguments to compile the generic function that inhabits the singleton type of `f` (`negate` in both of these cases) to a concrete function. This is why there are two versions of `negate` in the output in Listing 5. In other words, types *propagate* into generic functions – we didn't need to compile `negate` explicitly. This also explains the error printed on line 4.3-4.4: when this type was inadvertently assigned to the first argument `input`, the indexing operation on line 1.6 resulted in an error. A generic function can only be *statically* indexed by a list of types to turn it into a concrete function, not *dynamically* indexed with a value of type `clx.size_t` (the return type of the OpenCL primitive function `get_global_id`).

In effect, this scheme enables higher-order functions even when targeting languages, like OpenCL, that have no support for higher-order functions (OpenCL, unlike C99, does not support function pointers). Interestingly, because they have a singleton type, they are higher-order but not first-class functions. That is, the type system would prevent you from creating a heterogeneous list of generic functions. Concrete functions, on the other hand, can be given both a singleton type and a true function type. For example, `listing2.negate[[clx.int]]` could be given type `ace.Arrow(clx.int, clx.int)`. The base determines how to convert the Ace arrow type to an arrow type in the target language (e.g. a function pointer for C99, or an integer that indexes into a jump table constructed from knowledge of available functions of the appropriate type in OpenCL).

Type assignment to generic functions is similar in some ways to template specialization in C++. In effect, both a template header and type parameters at call sites are being generated automatically by Ace. This simplifies a sophisticated feature of C++ and enables its use with other targets like OpenCL.

### 2.6 Implicit Compilation and Interactive Execution

A common workflow for *professional end-user programmers* (e.g. scientists and engineers) is to use a simple scripting language for orchestration, small-scale data analysis and visualization and call into a low-level language for performance-critical sections. Python is both designed for this style of use and widely adopted for such tasks [25, 28]. Developers can call into native functions using Python's foreign function interface (FFI), for example. A more recent trend is to generate and compile code without leaving Python, using a Python wrapper around a compiler. For example, `weave` works with C and C++, and `pycuda` and `pyopencl` work with CUDA and OpenCL, respectively [20]. The OpenCL language was designed for this workflow, exposing a retargetable compiler and data management routines as an API, called the *host API* [14]. The `pyopencl` library exposes this API and supports basic interoperability with `numpy`, a package for safely manipulating contiguously-allocated numeric arrays in Python [20].

Ace supports a refinement to this workflow, as an alternative to the `acec` compiler described above, for targets that have wrappers like this available, including `clx.opencl`. Listing 6 shows an example of this workflow where the user chooses a compute device

**Listing 6** [`listing6.py`] A full OpenCL program using the `clx` Python bindings, including data transfer to and from a device and direct invocation of a generic function, `map`.

```
1  import listing1, listing2, examples.clx as clx, numpy
2
3  clx.opencl.ctx = clx.Context.for_device(0, 0)
4
5  input = numpy.ones((1024,1024))
6  d_input = clx.to_device(input)
7  d_output = clx.alloc(like=input)
8
9  listing1.map(d_input, d_output, listing2.negate,
10   global_size=d_in.shape)
11
12 assert (cl.from_device(d_out) == input * -1).all()
```

(line 6.3), constructs a `numpy` array (line 6.5), transfers it to the device (line 6.6), allocates an empty equal-sized buffer for the result of the computation (line 6.7), launches the generic kernel `map` from Listing 1 with these device arrays as well as the function `negate` from Listing 2 (line 6.9) choosing a number of threads equal to the number of elements in the input array (line 6.10), and transfers the result back into main memory to check that the device computed the expected result (line 6.12).

For developers experienced with the usual OpenCL or CUDA workflow, the fact that this can be accomplished in a total of 6 statements may be surprising. This simplicity is possibly largely due to implicit tracking of types throughout the code. First, `numpy` keeps track of the type, shape and order of its arrays. The type of `input`, for example, is `numpy.double` by default, its shape is `(1024,1024)` and its order is row-major by default. The `pyopencl` library that our mechanism is built atop uses this information to automatically call the underlying OpenCL host API function for transferring byte arrays to the device without requiring the user to calculate the size. Our wrapper of `pyopencl` further retains this information in the Python wrappers around the device arrays, `d_input` and `d_output`. The Ace active type of such wrappers can be designated to be an instance of `clx.NPArray` parametermized by this metadata. This type knows how to typecheck and translate operations like indexing automatically (see Sec. 3.1).

This allows us to call the generic function `map` directly on these Python data structures (as well as the generic function `negate`) without first requiring an explicit type assignment, like we needed when using `acec` above. In other words, dynamic types and other metadata can propagate from Python data structures into an Ace generic function as static type information, in the same manner as it propagated *between* generic functions in the previous section. In both cases, typechecking and translation of `map` happens the first time a particular type assignment is encountered and cached for subsequent use. When called from Python, the generated OpenCL source code is also compiled for the device we selected using the OpenCL host API's compiler infrastructure, and cached.

The same program written using the OpenCL C API directly is an order of magnitude longer and significantly more difficult to comprehend. OpenCL not support higher-order functions nor is there any way to write `map` in a type-generic manner. If we instead use the `pyopencl` library and apply the techniques described in [20], the program is still twice as large and less readable than this code. Both the `map` and `negate` functions must be explicitly specialized with the appropriate types using string manipulation techniques. Higher order functions are still not available, and must also be simulated by string manipulation. That approach also does not permit the use any of the language extensions that Ace enables (e.g. the type for `numpy` arrays, which ensures that indexing respects ordering; see Sec. 4 for more interesting possibilities).

## 3. Extensibility

The core of Ace consists of about 1500 lines of Python code implementing its primary concepts: generic functions, concrete functions, active types, active bases and active targets. The latter three comprise Ace's extension mechanism. Extensions provide semantics to, and govern the compilation of, Ace functions, rather than logic in Ace's core.

### 3.1 Active Types

Active types are the primary means for extending Ace with new abstractions. An active type, as mentioned previously, is an instance of a class implementing the `ace.ActiveType` interface. Listing 7 shows an example of such a class: the `clx.Cplx` class used in Listing 3, which implements the logic of complex numbers. The constructor takes as a parameter any numeric type in `clx` (line 7.2).

#### 3.1.1 Dispatch Protocol

In a compiler for a monolithic language, there would be a *syntax-directed* protocol governing typechecking and translation. In a compiler written in a functional language, for example, one would declare datatypes that captured all forms of types and expressions, and the typechecker would perform exhaustive case analysis over the expression forms, so all the semantics would be implemented in one place. The visitor pattern typically used in object-oriented languages implements essentially the same protocol. This does not work for an extensible language because new cases and logic need to be added modularly, in a safely composable manner.

Instead of taking a syntax-directed approach, the Ace compiler's typechecking and translation phases take a *type-directed approach*. When encountering a compound term (e.g. `e1[e2]`), the compiler defers control over typechecking and translation to the active type of a designated subexpression (e.g. `e1`) determined by Ace's fixed *dispatch protocol*. Below are examples of these choices. Due to space constraints, we do not show the full protocol.

- Responsibility over **attribute access** (`e.attr`), **subscripting** (`e[e1]`) and **calls** (`e(e1, ..., en)`) and **unary operations** (e.g. `-e`) is handed to the type recursively assigned to `e`.
- Responsibility over **binary operations** (e.g. `e1 + e2`) is first handed to the type assigned to the left operand. If it indicates a type error, the type assigned to the right operand is handed responsibility, via a different method call. Note that this operates like the corresponding rule in Python's *dynamic* operator overloading mechanism; see Sec. 5 for a discussion.
- Responsibility over **constructor calls** (`[t](e1, ..., en)`), where `t` is a *compile-time Python expression* evaluating to an active type, is handed to that type. If `t` evaluates to a *family* of types, like `clx.Cplx`, the active type is first generated via a class method, as discussed below.

#### 3.1.2 Typechecking

When typechecking a compound expression or statement, the Ace compiler temporarily hands control to the object selected by the dispatch protocol by calling the method `type_`$X$, where $X$ is the name of the syntactic form, taken from the Python grammar [1] (appended with a suffix in some cases).

For example, if `c` is a complex number, then `c.ni` and `c.i` are its non-imaginary and imaginary components, respectively. These expressions are of the form `Attribute`, so the typechecker calls `type_Attribute` (line 7.7). This method receives the compilation context, `context`, and the abstract syntax tree of the expression, `node` and must return a type assignment for the node, or raise an `ace.TypeError` if there is an error. In this case, a type assignment is possible if the attribute name is either `"ni"` or `"i"`, and an error is raised otherwise (lines 7.8-7.10). We note that error messages are an important and sometimes overlooked facet of ease-of-use [22]. A common frustration with using general-purpose abstraction mechanisms to encode an abstraction is that they can produce verbose and cryptic error messages that reflect the implementation details, rather than the semantics.

Complex numbers also support binary arithmetic operations partnered with both other complex numbers and with non-complex numbers, treating them as if their imaginary component is zero. The typechecking rules for this logic is implemented on lines 7.17-

**Listing 7** [in `examples/clx.py`] The active type family `Ptr` implements the semantics of OpenCL pointer types.

```
1  class Cplx(ace.ActiveType):
2    def __init__(self, t):
3      if not isinstance(t, Numeric):
4        raise ace.InvalidTypeError("<error message>")
5      self.t = t
6
7    def type_Attribute(self, context, node):
8      if node.attr == 'ni' or node.attr == 'i':
9        return self.t
10     raise ace.TypeError("<error message>", node)
11
12   def trans_Attribute(self, context, target, node):
13     value_x = context.trans(node.value)
14     a = 's0' if node.attr == 'ni' else 's1'
15     return target.Attribute(value_x, a)
16
17   def type_BinOp_left(self, context, node):
18     return self._type_BinOp(context, node.right)
19
20   def type_BinOp_right(self, context, node):
21     return self._type_BinOp(context, node.left)
22
23   def _type_BinOp(self, context, other):
24     other_t = context.type(other)
25     if isinstance(other_t, Numeric):
26       return Cplx(c99_binop_t(self.t, other_t))
27     elif isinstance(other_t, Cplx):
28       return Cplx(c99_binop_t(self.t, other.t))
29     raise ace.TypeError("<error message>", other)
30
31   def trans_BinOp(self, context, target, node):
32     r_t = context.type(node.right)
33     l_x = context.trans(node.left)
34     r_x = context.trans(node.right)
35     make = lambda a, b: target.VecLit(
36       self.trans_type(self, target), a, b)
37     binop = lambda a, b: target.BinOp(
38       a, node.operator, b)
39     si = lambda a, i: target.Attribute(a, 's'+str(i))
40     if isinstance(r_t, Numeric):
41       return make(binop(si(l_x, 0), r_x), si(r_x, 1))
42     elif isinstance(r_t, Cplx):
43       return make(binop(si(l_x, 0), si(r_x, 0)),
44         binop(si(l_x, 1), si(r_x, 1)))
45
46   @classmethod
47   def type_New(cls, context, node):
48     if len(node.args) == 2:
49       t0 = context.type(node.args[0])
50       t1 = context.type(node.args[1])
51       return cls(c99_promoted_t(t0, t1))
52     raise ace.TypeError("<error message>", node)
53
54   @classmethod
55   def trans_New(cls, context, target, node):
56     cplx_t = context.type(node)
57     x0 = context.trans(node.args[0])
58     x1 = context.trans(node.args[1])
59     return target.VecLit(cplx_t.trans_type(target),
60       x0, x1)
61
62   def trans_type(self, target):
63     return target.VecType(self.t.trans_type(target),2)
```

7.29. Because arithmetic operations are meant to be symmetric, the dispatch protocol checks both subexpressions for support, favoring the left to ensure that the semantics remain deterministic. In either position, the implementation begins by recursively assigning a type to the other operand in the current context via the `context.type` method (line 7.24). If supported, it applies the C99 rules for arithmetic operations to determine the resulting type (not shown).

Finally, a complex number can be constructed inside an Ace function using Ace's special constructor form: `[clx.Cplx](3,4)` represents $3 + 4i$, for example. The term within the braces is evaluated at *compile-time*. Because `clx.Cplx` evaluates not to an active type, but to a class, this form is assigned a type by handing control to the class object via the *class method* `type_New`. It operates as expected, extracting the types of the two arguments to construct an appropriate complex number type (lines 7.50-7.57), raising a type error if the arguments cannot be promoted to a common type according to the rules of C99 or if two arguments have not been provided (an exercise for the reader: modify this method to also allow a single argument for when the imaginary part is 0).

#### 3.1.3 Translation

Once typechecking a method is complete, the compiler enters the translation phase, where terms in the target language are generated from Ace terms. Terms in the target language are generated by calling methods of the *active targets*. The translation phase operates similarly to typechecking, using the dispatch protocol to invoke methods named `trans_`$X$. These methods have access to the context and node just as during typechecking, as well as the target.

As seen in Listing 5, we are implementing complex numbers internally using OpenCL vector types, like `int2`. Let us look first at `trans_New` on lines 7.54-7.60, where new complex numbers are translated to vector literals by invoking `VecLit` from the active target, which internally will generate the necessary OpenCL string for that form. The `trans_type` method of the `ace.ActiveType` is used to associated a type in the target language with an active type. For it to be possible to reason compositionally about the correctness of compilation, all complex numbers must translate to terms in the target language that have this target type. Ace supports a mode where this *representational consistency* is dynamically checked during compilation (this requires that the active target know how to assign types to terms in the target language, which can be done only for our OpenCL target as of this writing).

The translation methods for attributes and binary operations proceed in a straightforward manner. The context provides a method, `trans`, for recursively determining the translation of subexpressions as needed. Of note is that the translation methods can assume that typechecking succeeded. For example, the implementation of `trans_Attribute` assumes that if `node.attr` is not `'ni'` then it must have been `'i'` on line 7.14, consistent with the implementation of `type_Attribute` above it. Typechecking and translation are separated into two methods to emphasize that typechecking is not target-dependent and to allow for typing rules that require generating types for hypothetical terms, where the overhead of the translation might be better avoided.

### 3.2 Active Bases

Each generic function is associated with an active base, which is an object implementing the `ace.ActiveBase` interface. The active base specifies the *base semantics* of that function. It controls the semantics of statements and expressions that do not have a clear "primary" subexpression for the dispatch protocol to defer to. A base is handed control over typechecking of statements and expressions in the same way as active types: via `type_`$X$ and `trans_`$X$ methods. It also initializes the context and governs the semantics of variables. Each function can have a distinct base semantics.

Literals are the most prominent form given their semantics by an active base. Our example active base, `clx.base`, assigns integer literals the type `clx.int32` while floating point literals have type `clx.double`, consistent with the semantics of OpenCL and C99. The `clx.base` object is an instance of `clx.Base` that is pre-constructed for convenience. Alternative bases can be generated via different constructor arguments. For example, `clx.Base(flit_t=clx.float)` is a base semantics where floating point literals have type `clx.float`. This is useful because some OpenCL devices do not support double-precision numbers, or impose a significant performance penalty for their use. Indeed, to even use the `double` type in OpenCL, a flag must be toggled by a `#pragma` (The OpenCL target we have implemented inserts this automatically when needed, along with some other flags, and annotations like `kernel`). Similarly, for some applications, avoiding accidental overflows is more important than performance. Arbitrary-precision integers can be implemented as an active type (not shown) and the base generates the constructor call form, described above, around integers to support this.

Another role that the active base can play is to provide operators that do not need to be imported. The semantics of `get_global_id` and `printf`, for example, are provided by `clx.base`. In fact, the base provides a richer semantics for them than the underlying implementation, as we will show in the following section. It is not strictly necessary that the base provide these – they could have been imported from `clx` and used by their qualified name. A base which does not provide them without import can be generated by passing the `primitives=False` flag in.

### 3.3 Active Targets

An active target, which we show being used in the translation logic described above, is an instance of `ace.ActiveTarget`. It has two primary roles in Ace: 1) it provides an API for code generation to a target language, providing term and type constructors for use during translation (and, to support representational consistency checks, a type system implementation); 2) it provides a bridge to the underlying interoperability API when a generic or concrete function is launched directly from Python, as described in Sec. 2.6.

An active type or active base can support multiple targets if desired by simply examining it during translation (e.g. by performing capability checks using Python's `hasattr` function) and providing alternative code paths for different combinations of capabilities. Alternatively, an active backend can implement the interfaces available in a different back end and generate code for them in a different way. Our implementation of OpenCL's type system as a collection of active types and an active base does not explicitly support cross-compilation to a CUDA target (though it would be possible to modify it to do so), but our CUDA target does provide partial support for the OpenCL code generation API.

### 3.4 Compositional Reasoning

Every statement and expression in an Ace function is governed by exactly one active type, determined by the dispatch protocol, or by the single active base associated with the Ace function. The representational consistency check ensures that compilation is successful without requiring that types that abstract over other types (e.g. container types) know about their internal implementation details. Together, this permits compositional reasoning about the semantics of Ace functions even in the presence of many extensions. This stands on contrast to many prior approaches to extensibility, where extensions could insert themselves into the semantics in conflicting ways, making the order of imports matter (see Sec. 5).

**Listing 8** [datatypes_t.py] An example using statically-typed functional datatypes.

```
1  import ace, ace.python as py, examples.fp as fp
2
3  def Tree(name, a):
4    t = fp.Datatype(name)
5    t.cases = {
6      'Empty': fp.unit,
7      'Leaf': a,
8      'Node': fp.tuple(t, t)
9    }
10   t.close()
11   return t
12
13 DT = Tree('DT', py.dyn)
14
15 @ace.fn(py.Base(trailing_return=True))[[DT]]
16 def depth_gt_2(t):
17   t.case({
18     DT.Node(DT.Node(_), _): True,
19     DT.Node(_, DT.Node(_)): True,
20     _: False
21   })
22
23 @ace.fn(py.Base(main=True))[[]]
24 def __main__():
25   my_lil_tree = DT.Node(DT.Empty, DT.Empty)
26   my_big_tree = DT.Node(my_lil_tree, my_lil_tree)
27   assert not depth_gt_2(my_lil_tree)
28   assert depth_gt_2(my_big_tree)
```

**Listing 9** [datatypes.py] The dynamically-typed Python code generated by running `acec datatypes_t.py`.

```
1  class DT(object):
2    pass
3
4  class DT_Empty(DT):
5    pass
6
7  class DT_Leaf(DT):
8    def __init__(self, data):
9      self.data = data
10
11 class DT_Node(DT):
12   def __init__(self, data):
13     self.data = data
14
15 def depth_gt_2(x):
16   if isinstance(x, DT_Node):
17     if isinstance(x.data[0], DT_Node):
18       r = True
19     elif isinstance(x.data[1], DT_Node):
20       r = True
21   elif True:
22     r = False
23   return r
24
25 if __name__ == "__main__":
26   my_lil_tree = DT_Node(DT_Empty(), DT_Empty())
27   my_big_tree = DT_Node(my_lil_tree, my_lil_tree)
28   assert not depth_gt_2(my_lil_tree)
29   assert depth_gt_2(my_big_tree)
```

## 4. Expressiveness

Thus far, we have focused mainly on the OpenCL target and shown examples of fairly low-level active types: those that implement OpenCL's primitives (e.g. `clx.Ptr`), extend them in simple but convenient ways (e.g. `clx.Cplx`) and those that make interactive execution across language boundaries safe and convenient (e.g. `clx.NPArray`). Ace was first conceived to answer the question: *can we build a statically-typed language with the semantics of a C but the syntax and ease-of-use of a Python?* We submit that these examples (along with a large-scale simulator framework built using them, which we do not have space to detail here) have answered this question in the affirmative.

But Ace has proven useful for more than low-level tasks like programming a GPU with OpenCL. We now describe several interesting extensions that implement the semantics of primitives drawn from a range of different language paradigms, to justify our claim that these mechanisms are highly expressive.

### 4.1 Growing a Statically-Typed Python Inside an Ace

Ace comes with a target, base and type implementing Python itself: `ace.python.python`, `ace.python.base` and `ace.python.dyn`. These can be supplemented by additional active types and used as the foundation for writing actively-typed Python functions. These functions can either be compiled ahead-of-time to an untyped Python file for execution, or be immediately executed with just-in-time compilation, just like the OpenCL examples we have shown. Many of the examples in the next section support this target in addition to the OpenCL target we have focused on thus far.

### 4.2 Functional Datatypes

Listing 8 shows an example of the use of statically-typed functional datatypes alongside the Python implementation just described. It shows two syntactic conveniences that were not mentioned previously: 1) if no target is provided to `ace.fn`, the base can provide a default target (here, `ace.python.python`; 2) A concrete function can be generated immediately by providing a type assignment to `ace.fn`. Listing 8 generates Listing 9.

Lines 8.3-8.11 define a function that generates a recursive algebraic datatype representing a tree given a name and another Ace type for the data at the leaves. This type implemented by the active type family `fp.Datatype`. Case names and their types are provided programmatically on lines 8.5-8.10. These lines also show two more active type families: units (the type containing just one value), and immutable pairs. Line 8.13 calls this function with the Ace type for dynamic Python values, `py.dyn`, to generate a type, aliased `DT`. This type is implemented using class inheritance when the target is Python, as seen on lines 9.1-9.13. For C-like targets, a `union` type can be used (not shown).

The generic function `depth_gt_2` demonstrates two features. First, the base has been setup to treat the final expression in a top-level branch as the return value of the function, consistent with typical functional languages. Second, the `case` "method" on line 8.17 creatively reuses the syntax for dictionary literals to express a nested pattern matching construct. The patterns to the left of the colons are not treated as expressions (that is, a type and translation is never recursively assigned to them). The active type implements the standard algorithm for ensuring that the cases cover all possibilities and are not redundant. If the final case were omitted, for example, the algorithm would statically indicate an error, just as in statically-typed functional languages like ML and Haskell.

### 4.3 Nested Data Parallelism

Functional constructs have shown promise as the basis for a nested data-parallel parallel programming model. Many powerful parallel algorithms can be specified by composing primitives like `map` and `reduce` on persistent data structures like lists, trees and records. Data dependencies are directly encoded in these specifications, and automatic code generation techniques have shown promise in using this information to automatically execute these specifications on concurrent hardware and networks. The Copperhead programming language, for example, is based in Python as well and allows users to express functional programs over lists using common functional primitives, compiling them to CUDA code [6]. By combining active types and the metaprogramming facilities described in

Sec. 2 to implement optimizations, like fusion, on the typed syntax trees available from concrete functions, these same techniques can be implemented as an Ace library as well.

### 4.4 Structs, Unions, Records and Objects

Data structures like structs, unions, records and objects can all be implemented as Ace type families parameterized by a dictionary mapping field names to types. Each family differs slightly in the semantics of the operations available. Structs support mutation, for example, while records do not. Object systems typically introduce additional logic for calling methods, binding special variables like `this`, and accessing information through an inheritance hierarchy. Listing 10 shows an example of each of these. The prototypic object system delegates to a backing record if a field is not available in the struct. This example also demonstrates cross-compilation to C99, supported for a subset of operations in `clx`. All three abstractions are implemented as simple `structs`, as can be seen in Listing 11. This example also demonstrates the use of argument annotations to generate concrete functions (line 10.9), which is a feature only available when running Ace in Python 3.

### 4.5 Distributed Programming

Many distributed programming abstractions can be understood as implementing object models with complex forms of dynamic dispatch. For example, in Charm++, dynamic dispatch involves message passing over a dynamically load-balanced network [16]. While Charm++ is a sophisticated system, and we do not anticipate that implementing it as an Ace extension would be easy, it is possible to do so by targeting a system like Adaptive MPI, which exposes the Charm++ runtime system [17].

A number of recent languages designed for distributed programming on clusters use a partitioned global address space model, including UPC [5], Chapel [9] and others. These languages provide first-class support for accessing data transparently across a massively parallel cluster. Their type systems track information about *data locality* so that the compiler can emit more efficient code. The extension mechanism can also track this information in a manner analogous to how address space information is tracked in the OpenCL example above, and target an existing portable run-time such as GASNet [3].

#### 4.5.1 Units of Measure

A number of domain-specific type systems can be implemented within Ace as well. For example, prior work has considered tracking units of measure (e.g. grams) statically to validate scientific code [18]. This cannot easily be implemented using many existing abstraction mechanisms because this information should only be maintained statically to avoid excessive run-time overhead associated with tagging/boxing, and the typechecking logic is reasonably complex. The Ace extension mechanism allows this information to be tracked in the type system, but not included during translation, by a mechanism similar to how address space information is tracked with pointers. Because Ace extensions can use Python, the needed logic can be implemented directly.

## 5. Related Work

Libraries that contain compile-time logic have been called *active libraries* in prior proposals [34]. A number of projects, such as Blitz++, have taken advantage of the C++ preprocessor and template-based metaprogramming system to implement domain-specific optimizations [33]. In Ace, we replace these brittle mini-languages with a general-purpose language, Python, and significantly expand the notion of active libraries by consideration of types, base semantics and target languages as values (in this case, objects) in the compile-time metalanguage.

**Listing 10** `[ooclxfp.py]` An example combining structs and immutable records using a prototype-based object system, cross-compiled to C99. Uses Python 3 argument annotations.

```
1  import examples.clx as clx, examples.fp as fp,
2    examples.oo as oo
3
4  A = clx.Struct('A', {'x': clx.int})
5  B = fp.Record('B', {'y': clx.float})
6  C = oo.Prototypic('C', A, B)
7
8  @ace.fn(clx.base, clx.c99)
9  def test(input : C):
10   return input.x + input.y
```

**Listing 11** `[ooclxfp.c]` The C99 code generated by running `acec ooclxfp.py`.

```
1  typedef struct {
2      int x;
3  } A;
4
5  typedef struct {
6      float y;
7  } B;
8
9  typedef struct {
10     A self;
11     B proto;
12 } C;
13
14 float test(C input) {
15     return C.self.x + C.proto.y;
16 }
```

Generic functions are a novel strategy for *function polymorphism* – defining functions that operate over more than a single type. In Ace, generic functions are implicitly polymorphic and can be called with arguments of *any type that supports the operations used by the function*. This approach is related to structural polymorphism [21]. Structural types make explicit the requirements on a function, unlike generic functions, which are only given singleton types because the requirements can be defined arbitrarily by extensions. Structural typing can be compared to the more *ad hoc* approach taken by dynamically-typed languages like Python itself, sometimes called "duck typing". It is also comparable to the C++ template system, as discussed previously. Debugging type errors can be more difficult when there are many nested generic functions that were implicitly given type assignments. Type debuggers like `scalad` could help make this easier [26].

*Operator overloading* [32] and *metaobject dispatch* [19] are run-time protocols that translate operator invocations into function calls. The function is typically selected according to the type or value of one or more operands. These protocols share the notion of *inversion of control* with our strategy. However, our strategy is a *compile-time* protocol where the typechecking and translation semantics are implemented for different operators. Our dispatch protocol was designed to be conceptually similar to Python's operator overloading protocol [1].

There are several other language-internal extension mechanisms that have been described in the literature. These differ from our mechanism based primarily on active types in one of the following ways, summarized in the table in Figure 1:

- Our mechanism is itself implemented as a library, rather than as a language extension.
- Our mechanism reuses an existing language's syntax, rather than offering syntax extension support. As we saw in, for ex-

| Approach | Examples | Library | Extensible Syntax | Extensible Type System | Extensions Compositional | Alternative Targets |
|---|---|---|---|---|---|---|
| Active Types | Ace | ● | ○ | ● | ● | ● |
| Desugaring | SugarJ [12] | ○ | ● | ○ | ○ | ○ |
| Rule Injection | Qi, Typed Racket [31], Xroma [34] | some | ○ | ● | ○ | ○ |
| Static macros / Metaprogramming | Scala [4], MorphJ [15], OJ [30] MetaML [29], Template Haskell | ○ | ○ | ○ | ● | ○ |
| Cross-Compilation | Delite [8] | ● | ○ | ○ | ○ | ● |

**Figure 1.** Comparison to related approaches to language-internal extensibility.

ample, Listing 8, this can still be reasonably natural. However, some mechanisms provide true syntax extensions.

- Our mechanism permits true type system extensions. New types are not merely aliases, nor must their rules be admissible in some base type system. Term rewriting and macro systems do not handle types at all.
- As described in Sec. 3.4, our mechanism permits compositional reasoning. Techniques that allow global extensions to the syntax or semantics (e.g. SugarJ or rule injection systems like Xroma or Typed Racket) allow extensions so much control that they can interfere with one another or make reasoning about code difficult.
- Our mechanism allows users to control the target language of compilation from within libraries. Many other mechanisms are based fundamentally on rewriting mechanisms.

When the mechanisms available in an existing language prove insufficient, researchers and domain experts often design a new language. A number of tools have been developed to assist with this task, including compiler generators, language workbenches and domain-specific language frameworks (cf [13]). Extensible compilers can be considered a form of language framework as well due to the interoperability issues that relying on a compiler-specific extensions can introduce. It is difficult or impossible for these language-external approaches to achieve interoperability, because languages are not aware of each other's semantics.

## 6. Discussion

Static type systems are powerful tools for programming language design and implementation. By tracking the type of a value statically, a typechecker can verify the absence of many kinds of errors over all inputs. This simplifies and increases the performance of the run-time system, as errors need not be detected dynamically using tag checks and other kinds of assertions.

It is legitimate to ask, however, why dynamically-typed languages are so widely-used in multiple domains. Although slow and difficult to reason about, these languages generally excel at satisfying the criteria of **ease-of-use**. More specifically, Cordy identified the principle of *conciseness* as elimination of redundancy and the availability of reasonable defaults [11]. Statically-typed languages, particularly those that professional end-users are exposed to, are often verbose, requiring explicit and often redundant type annotations on each function and variable declaration, separate header files, explicit template headers and instantiation and other sorts of annotations. Dynamically-typed languages, on the other hand, avoid most of this overhead by relying on support from the run-time system. Ace was first conceived to explore the question: *does conciseness require run-time mechanisms, or can one develop a statically-typed language with the same usability profile?*

Rather than designing a new syntax, or modifying the syntax of an existing language, we chose to utilize, *without modification*, the syntax of an existing language, Python. This choice was not arbitrary, but rather a key means by which Ace satisfies extrinsic design criteria related to familiarity and tool support. Researchers often dismiss the importance of syntax. By repurposing a well-developed syntax, they no longer need to worry about the "trivial" task of implementing it.

Most programming languages are *monolithic* – a collection of primitives are given first-class treatment by the language implementation, and users can only creatively combine them to implement abstractions of their design. Although highly-expressive general-purpose mechanisms have been developed (such as object systems or functional datatypes), these may not suffice when researchers or domain experts wish to evolve aspects of the type system, exert control over the representation of data, introduce specialized run-time mechanisms, if defining an abstraction in terms of existing mechanisms is unnatural or verbose, or if custom error messages are useful. In these situations, it would be desirable to have the ability to modularly extend existing systems with new compile-time logic and be assured that such extensions will never interfere with one another when used in the same program.

Python does not truly prevent extensions from interfering with one another because it lacks, e.g., data hiding mechanisms. One type could change the implementation of another by replacing its methods, for example. But these kinds of conflicts do not occur "innocently", as conflicts between two libraries in SugarJ that use similar syntax might.

Ace has some limitations at the moment. Debuggers and other tools that rely not just on Python's syntax but also its semantics cannot be used directly, so if code generation introduces significant complexity that leads to bugs, this can be an issue. The OpenCL library we have implemented is a reasonably straightforward internalization of OpenCL itself, however, so debugging has not been a problem thusfar. We believe that active types can be used to control debugging, and plan to explore this in the future. We have also not yet evaluated the feasibility of implementing more advanced type systems (e.g. linear type systems, dependent type systems, flow-dependent type systems) using Ace.

Not all extensions will be useful. Indeed, some language designers worry that offering too much flexibility to users leads to abuse (this is, for example, widely credited as the reason why Java doesn't support operator overloading). We do not argue with this point. Instead, we argue that the potential for abuse must be balanced with the possibilities made available by a vibrant ecosystem of competing statically-typed abstractions that can be developed and deployed as libraries, and thus more easily evaluated in the wild. With an appropriate community process, this could lead to convergence via collections of curated, high-quality collections more quickly than is possible today, where most widely-adopted languages evolve quite slowly.

This paper is presented as a language design paper. The theoretical foundations of this work lie in type-level computation. We have developed a simplified, type-theoretic formalism of active typechecking and translation, where we prove the safety properties we have outlined here, as well as several additional ones that are only possible to achieve using a typed metalanguage. That work is currently in submission at ESOP 2014. The work described here is original and extends that mechanism in several directions: Ace supports a rich syntax, makes syntax trees available to extensions, supports a pluggable backend and per-function base semantics. It is implemented in an existing language as a library and supports a wide range of eminently practical extensions. We hope that it will serve as a useful tool both to researchers and in practice. The mechanisms described here can be supported be any language that offers some form of quotation of function ASTs and a reasonably flexible collection of syntactic forms. They are particularly useful when the language has a variety of interoperability layers with other languages, like Python does.

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