PoTo: A Hybrid Andersen's Points-to Analysis for Python

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ABSTRACT

As Python is increasingly being adopted for large and complex programs, the importance of static analysis for Python (such as type inference) grows. Unfortunately, static analysis for Python remains a challenging task due to its dynamic language features and its abundant external libraries. To help fill this gap, this paper presents PoTo, an Andersen-style context-insensitive and flow-insensitive points-to analysis for Python. PoTo addresses Python-specific challenges and works for large programs via a novel hybrid evaluation, integrating traditional static points-to analysis with concrete evaluation in the Python interpreter for external library calls. Next, this paper presents PoTo+, a static type inference for Python built on the points-to analysis. We evaluate PoTo+ and compare it to two state-of-the-art Python type inference techniques: (1) the static rule-based Pytype and (2) the deep-learning based DLInfer. Our results show that PoTo+ outperforms both Pytype and DLInfer on existing Python packages.

CCS CONCEPTS

• **Theory of computation → Semantics and reasoning**; • **Software and its engineering → Functionality**.

KEYWORDS

Python, machine learning libraries, interprocedural analysis

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1 INTRODUCTION

Points-to analysis is a fundamental static analysis that determines what objects a reference variable may point to. It has a wide variety of applications (aka. *client* analyses), including call graph construction, type inference, debugging, and security vulnerability detection. Essentially all interesting questions one could ask about a program require some form of points-to information. Therefore, points-to analysis has been studied extensively in the context of mainstream languages such as C, C++, Java, and JavaScript.

Surprisingly, points-to analysis (and more generally static analysis) for Python have received less attention, despite Python's popularity. Concrete client applications in Python include call graph construction, type inference, and early error reporting.

This paper presents PoTo, an Andersen-like point-to analysis for Python. Andersen's analysis [2] is a classical flow-insensitive, context-insensitive, and inclusion-constraint-based analysis. It computes a points-to graph Pt where the nodes are reference variables and heap objects, and the edges represent points-to relations. For example, an edge $x \rightarrow o$ represents that x refers to heap object o (i.e., reference x stores the address of o), and $o_1 \xrightarrow{f} o_2$ represents that field f of o_1 refers to o_2.

While PoTo leverages well-known techniques, it also adapts to the unique challenges of Python: complex syntax and module system, dynamic semantics, and ubiquitous use of external libraries whose code is unavailable. First, our solution presents principled translation from Python source into the 3-address code intermediate representation demanded by points-to analysis. It specifies explicitly which Python features are handled precisely and which are handled approximately. Second, a novelty of PoTo is *hybridization.* We observe that many expressions, particularly ones stemming from external libraries and built-in functions, are available for *concrete evaluation* but are unavailable for standard *abstract evaluation* by virtue of their code being unavailable. Therefore we *concretely evaluate* the expressions and propagate the concrete objects through the points-to graph. This yields more information during inclusion constraint resolution and improved program coverage.

We evaluate PoTo on concrete type inference. We choose type inference because there has been significant interest in the problem in recent years. In addition to traditional approaches such as Pytype [8], there has been significant advance in deep-learning-based approaches, e.g., [1, 19, 28]. PoTo+ is the type inference client that largely draws types from PoTo's result: given $Pt(x)$ computed by the points-to analysis, the type of x is the union of the types of objects $o \in Pt(x)$. We compare PoTo+ against (1) Pytype [8], arguably the most advanced rule-based type inference tool, and (2) DLInfer [28], a state-of-the-art deep-learning-based tool, on a benchmark suite

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of Python packages ranging from 3,556 to 285,515 lines of code. Our results show that PoTo+ is comparable to Pytype and both techniques outperform DLInfer in terms of coverage (i.e., percentage of variables for which a type is reported) and correctness of inferred types. Furthermore, PoTo scales better than Pytype.

The contributions of our work are as follows:

- PoTo, the first Andersen-style points-to analysis for Python.
- Hybridization weaving concrete and abstract evaluation.
- PoTo+, a type inference client, and its extensive evaluation.

The paper is organized as follows. Section 2 presents the problem statement and an overview of our solution. Section 3 formalizes the solution: it presents a minimal Python syntax, the 3-address code interpretation semantics, and constraint resolution. Section 4 presents the detailed evaluation, Section 5 discusses threads to validity, and Section 6 elaborates on related work. Section 7 concludes.

2 PROBLEM STATEMENT AND OVERVIEW

In short, the problem at hand is to design an Andersen-style points-to analysis for Python and *scale the analysis to large real-world Python packages*. Andersen's points-to analysis is a classical static analysis problem. It has been studied and implemented for large code bases of C, C++, Java, JavaScript and other languages. The analysis is a whole-program flow-insensitive and context-insensitive analysis that tracks flow of values via inclusion constraints. E.g., an assignment statement `x = y` triggers an inclusion constraint $Pt(\mathtt{y}) \subseteq Pt(\mathtt{x})$ indicating that the points-to set of `y` flows to the points-to set of `x`.

There are numerous challenges for a static analysis for Python, including Andersen's analysis. First, such analysis is based on a 3-address code intermediate representation (IR) serving as the foundation for the inclusion constraints. Translation from high-level C, C++, Java and JavaScript code into 3-address code is well-studied and there are mature tools that provide the translation, notably LLVM [12], Soot [24], WALA [11], and Doop [22]. Surprisingly, static analysis for Python is largely ad-hoc AST-based analysis with each new work embedding its own interpretation of Python AST constructs and translation (if any) of those constructs into a 3-address code IR. Translating Python AST constructs into a 3-address code IR is challenging due to (1) the complex syntax and dynamic semantics of those constructs, and (2) Python's rich module system and scoping issues arising from it. For example, even translation of a mundane AST construct such as Subscript, e.g., `a[index_expr]`, is non-trivial as code may override `__getitem__` with arbitrary semantics. A choice to treat Subscript in the standard way, i.e., element access of a list-like structure, introduces unsoundness.

The second key challenge to a static analysis is use of external libraries. Whole-program static analysis generally assumes that library code is available, and this is clearly not the case for Python.

Another challenge is that Python supports functions and classes as first-class values that flow throughout the program, and constraint resolution ought to account for that. In contrast, Andersen's analysis for Java, the closest related work, does not consider functions or classes as first-class values.

This paper addresses the three challenges. We consider principled translation of AST constructs for the purposes of Andersen's analysis and develop a hybrid analysis that alleviates the problem arising from the use of external libraries. We extend the constraint system of Andersen's analysis with handling of class objects and function objects as first-class values.

```python
import re

def url_regex():
  regex_cache = None
  if regex_cache is None:
    regex_cache = re.compile(r"p")
  return regex_cache

def str_validator(value):
  if isinstance(value,str):
    return value.value
  else:
    return value

def validate(value):
  url = str_validator(value)
  m = url_regex().match(url)
  if m.end() != len(url):
    raise Exception(m.end())

def main():
  validate("p abcd")
```

(a) Python source

```
import re # External import

def url_regex():
  regex_cache = None
  regex_cache = (const, <class 're.Pattern'>, ...)
  url_regex_ret = regex_cache

def str_validator(value):
  str_validator_ret = value.value
  str_validator_ret = value

def validate(value):
  url = str_validator(value)
  t1 = url_regex()
  t2 = t1.match
  m = t2(url)
  t3 = m.end
  t4 = t3()
  t5 = len(url)
  t6 = (const, <class 'Exception'>,...)
  t7 = m.end
  t8 = t7()
  t9 = t8(t7)
```

(b) 3-address code

Figure 1: Illustrating example, adapted from DLInfer [28].

1.	x = object	*new assignment*
2.	x = y	*copy propagation*
3.	x.f = y	*field write*
4.	x = y.f	*field read*
5.	x = y(z)	*closure call*

Figure 2: 3-address code statements.

Consider the example in Figure 1, adapted from DLInfer, a recent paper on neural type inference for Python. Our analysis has two core phases (PoTo), followed by a client analysis phase (PoTo+):

- Phase 1: Python source ⟶ 3-address code
- Phase 2: 3-address code ⟶ Points-to graph
- Phase 3 (client): Points-to graph ⟶ Concrete type assignment

Phase 1 takes as input Python source code and produces 3-address code; this phase works at the granularity of a function. Phase 2 processes the 3-address statements as inclusion constraints computing the points-to graph. The two phases are intertwined — roughly, the analysis starts at the main function and immediately invokes Phase 1 on main generating 3-address code for main; it then invokes Phase 2 to solve the 3-address code for main. As new functions become reachable, the analysis invokes 3-address code generation, then it proceeds to solve the constraints until the points-to graph reaches a fixpoint. As expected, one can implement many client analyses on top of the points-to results. Phase 3 focuses on concrete (i.e., non-polymorphic) type inference as a client analysis.

The first phase does principled translation of Python AST constructs into the standard 3-address statements shown in Figure 2.

For example, the Python source in Figure 1(a) Line 17 translates into the 3-address sequence of statements in Figure 1(b) Lines 14–16. A novelty in our treatment is the weaving of concrete evaluation into 3-address code translation and later constraint resolution. During translation, the analysis concretely evaluates every expression in its enclosing import environment. If evaluation succeeds, translation returns the resulting constant; otherwise, it proceeds recursively and returns the corresponding 3-address code statements. For example, in Figure 1(a) Line 6, the right-hand-side evaluates into a concrete object: (const, <class 're.Pattern'>, ...) in Figure 1(b) Line 5. Note that as it is standard for flow-insensitive analysis, the translation ignores control flow and basic blocks. Each function in Figure 1(b) is a straight-line sequence of 3-address statements. Suffix `_ret` indicates the function's return value (e.g., `str_validator_ret`).

The second phase of the analysis solves the 3-address statements as inclusion constraints, incorporating (1) class and function objects as first-class values, and (2) concrete evaluation. The analysis maintains *abstract objects* (constructed from code in the package under analysis) and *concrete objects* (constructed from concrete evaluation). Abstract objects, in turn, fall into three categories: *meta-class* objects, *function* objects (more precisely closure objects), and *data* objects. The analysis maintains an abstract reference environment, which is the package-under-analysis environment, and uses it to resolve names defined in the package.

When processing a call 3-address statement or a field access statement, the analysis retrieves each object in the points-to set of the receiver variable. Roughly speaking, if the function object at the call is an abstract one, the analysis proceeds with abstract evaluation. If it is a concrete one, it attempts concrete evaluation. For example, in `url = str_validator(value)`, the analysis examines the points-to set of `str_validator` and retrieves the abstract function object representing the `str_validator` function. This triggers abstract evaluation and (standard) addition of the points-to set of `str_validator_ret` (the special return variable) to the points-to set of the left-hand-side variable `url`. Eventually, the points-to set of `url` becomes (const, <class 'str'>, 'p abcd'). Concrete evaluation of `t2 = t1.match` returns the concrete closure object corresponding to the match function, and finally concrete evaluation of `m = t2(url)` returns a concrete `re.Match` object. The hybrid analysis infers concrete types for identifiers `url` and `m`, respectively <class 'str'> and <class 're.Match'>, while Pytype reports only the fall-through type Any for both.

The next section grounds the PoTo analysis around a minimal Python syntax and formalizes the two core phases (the third phase being the client analysis PoTo+).

3 SYNTAX AND SEMANTICS

Recent work defines syntax for a subset of Python and a corresponding interpretation semantics for the purposes of weakest precondition inference [20]. A notable idea in this work is the separation of Python constructs into *interpreted* and *uninterpreted* ones. Interpreted constructs are handled precisely following the construct's intended semantics. Uninterpreted constructs are captured by a syntactic structure *Other* and are subject to fall-through interpretation. Fall-through interpretation ignores the semantics the construct carries and recursively interprets its components; it is generally neither sound nor precise.

```
e  ::=  c | x | e.x | e[e] | e(e, ..., e)
     |  [e, ..., e] | {e: e, ..., e: e} | (e, ..., e)
     |  [e for x, ..., x in e if e]
     |  {e:e for x, ..., x in e if e}
     |  Other (e, ..., e)

s  ::=  pass | x = e | e.x = e | e[e] = e
     |  s ; s | for e in e: s
     |  def f(x, ..., x): s ; return e
     |  class C(e, ..., e): s
     |  Other (s, ..., s)

i  ::=  import p | from p import x | i as x | i ; i

m  ::=  i ; s
```

Figure 3: Syntax of a subset of Python.

In this paper, we follow the idea of separating constructs into interpreted and *Other* but differ in important ways as our goal is interprocedural flow- and context-insensitive points-to analysis rather than weakest precondition inference. Unlike [20], we track object creation and flow of values and construct a call graph on the fly. Flow-insensitive points-to analysis demands a different set of interpreted constructs and typically a different interpretation.

Section 3.1 defines the syntax for the purposes of flow-insensitive points-to analysis, Section 3.2 defines the interpretation that generates 3-address code, and Section 3.3 presents Andersen-style constraint resolution, highlighting Python-specific semantics.

3.1 A Minimal Python Syntax

Figure 3 specifies the syntax which grounds the analysis. An expression e can be a constant c (`42` or `"foo"`), a variable (`x`), an attribute access (`x.foo`), a subscript access (`x["bar"]`), a list, a tuple, a dictionary, a list comprehension (`[2*x for x in range(10)]`) or a dictionary comprehension (`{x:f(x)for x in range(x)}`). Other Python expressions are left uninterpreted $Other\,(e_1, ..., e_n)$.

A statement s can be pass, the assignment of either a variable (`x = 42`), an attribute (`x.foo = 42`), or a subscript (`x["bar"] = 42`), a sequence, a loop, a function definition, or a class definition. Other Python statements are left uninterpreted $Other\,(s_1, ..., s_n)$.

A module m starts with a sequence of import i, import p or from p import x, with an optional alias name i as x, followed by a statement. A package under analysis is a sequence of modules.

To simplify the presentation, we focus here on a simple subset of Python, but our analysis is implemented on top of the full Python AST. In particular, we left out complex left-hand side expressions in assignements (e.g., `a, *(b, c)= (1, (2, 3), 4)`), variable length arguments and keywords arguments to simplify the presentation.

3.2 3-address Code Generation

3-address-code translation takes as input the Python source (i.e., AST) of a function and produces a sequence of 3-address-code statements of the form in Figure 2.

3.2.1 Environment and Interpretation Functions. The analysis interprets expressions and statements in an *abstract* reference environment split into two components: Γ and Γ_0. Γ is a *local* reference environment associated to the enclosing function. It is a map of (id,t) tuples where id is a local and t is the *analysis variable* representing the local. Γ_0 is the *global* reference environment mapping identifiers for module-level constructs to analysis variables representing those constructs. In addition, there is an *external* environment, Γ_{ext}, necessary for concrete evaluation. We analyze imports and group them into two categories: (1) internal imports are relative imports (e.g., `from ..metrics import get_scorer`) and ones referencing the analysis package, and (2) the remaining external imports (e.g., `import re`). External imports comprise Γ_{ext}.

The interpretation of a statement $\mathcal{I}(s, \Gamma)$ returns a pair (Γ', S) where Γ' is the augmented local environment resulting from the interpretation of s into 3-address code, and S is *the sequence of 3-address statements* corresponding to s. E.g., $\mathcal{I}$(x = y.f.g, [(y, t1)]) returns the augmented environment [(x,t2), (y,t1)] and the following sequence of 3-address statements: t4 = t1.f; t3 = t4.g; t2 = t3. Here t1 and t2 are the analysis variables associated with local variables y and x respectively.[1] We leave Γ_0 and Γ_{ext} implicit in the writeup as they are uniquely defined for each statement under interpretation.

The interpretation of an expression $\mathcal{I}(e, \Gamma)$ returns a pair (V, S) where V is *a set of analysis variables* and S is the sequence of 3-address statements corresponding to e. E.g., $\mathcal{I}$(y.f.g, [(y, t1)]) returns fresh variable t3 and the sequence of 3-address statements t4 = t1.f; t3 = t4.g.

Φ is the environment of interpreted functions: a mapping from a function definition (Python AST FunctionDefs in the implementation) to a pair (Γ, S), where Γ is the local reference environment resulting from the translation of the function definition and S is the sequence of 3-address statements corresponding to the function body.

3.2.2 Worklist Algorithm. The analysis uses a worklist algorithm:

 # Initialize Γ_0*:*
$\Gamma_0 = [], \Phi = \{\}$
for ⟨module M : i; s⟩ in package under analysis
  for ⟨class C(...): ...⟩ in s: $\Gamma_0 \leftarrow [(M.C, \text{t})] + \Gamma_0$, t is fresh
  for ⟨def f(...): ...⟩ in s: $\Gamma_0 \leftarrow [(M.f, \text{t})] + \Gamma_0$, t is fresh
  # Imports from p import x′ x′ as x are implicit assignments
  for x = ... in s: $\Gamma_0 \leftarrow [(M.x, \text{t})] + \Gamma_0$, t is fresh
 # Next, compute class hierarchy and MRO:
$H \leftarrow C3(\Gamma_0)$ *# H maps (⟨class C(...): ...⟩, f) to ⟨def f(...): ...⟩*
 # Interpret main and add to worklist:
Φ[⟨def *main*(...): s⟩] $\leftarrow \mathcal{I}(s, [])$
$W \leftarrow$ {⟨def *main*(...): s⟩} *# Entry point*
 # Interpret module initializers and add to worklist:
for ⟨module M : ...⟩ in package under analysis
  Φ[⟨def M.*module_init*(...): i; s⟩] $\leftarrow \mathcal{I}(i; s, [])$
  $W \leftarrow$ {⟨def M.*module_init*(...): i; s⟩} *# Entry points*
 # Solve constraints in reachable functions:
while $W \neq \emptyset$
  ⟨def f(...): ...⟩ $\leftarrow$ remove function from W
  for c in Φ[⟨def f(...): ...⟩][1]: $W \leftarrow W + c.solve()$

[1] In code examples we sometimes ignore analysis variables and use the source-level identifier directly.

3.2.3 Global Environment Initialization. The analysis first initializes a global environment Γ_0 that contains mappings for identifiers of module-level constructs, $M.f$ (functions), $M.C$ (classes), and $M.x$ (identifier definitions) to their corresponding analysis variables. The scope of these constructs spans the entire package, hence the analysis augments the environment and makes these constructs available during 3-address code generation. This is similar to the let-rec construct in functional programming which extends the scope for let-bound identifiers across all right-hand-side expressions. Note that initialization does not interpret functions, classes and right-hand-side of assignments; these are interpreted during reachability analysis.

3.2.4 Class Hierarchy Analysis. Next, the analysis computes H using the C3 linearization algorithm for method resolution with multiple inheritance [3]. H is a mapping from a pair of class definition ⟨class C(...): ...⟩ and function name f to the corresponding function definition ⟨def f(...): ...⟩ resulting from a lookup in the *Method Resolution Order* (MRO) of C. Additionally, the step creates a (meta-cls, ⟨class C(...): ...⟩) object for each module-level class definition and associates the corresponding analysis variable t to that object. In other words, this step creates an initial set of points-to edges which allows for dynamic data object creation during the second phase of the analysis.

3.2.5 Iteration. As it is customary for whole-program analysis, the analysis starts from a main function. It translates main and all module initializers into 3-address code (the calls to $\mathcal{I}(s, [])$) and adds them to the worklist. The analysis removes a function from the worklist and processes the 3-address statements c for that function. $c.solve()$ solves the semantic constraints associated to c which has side effects on the 3-address code environment Φ and points-to graph Pt. A call statement triggers interpretation and placement on the worklist of the callee function and it is an invariant that when a function is removed from the worklist, its three address code is available in Φ.

$c.solve()$ returns a minimal set of functions that are affected by solving constraint c. For example, if c is the 3-address code statement t1 = t2 and solving it changes the points-to graph of t1, *solve* returns the enclosing function of the statement. A change in the points-to graph due to t1.f = t2 returns all functions in Φ, as the effect of new objects added to Pt(o.f), where o is an object in the points-to set of t1, may propagate to arbitrary functions.

3.2.6 Concrete Evaluation. Recall that a key feature of our analysis is concrete evaluation. $\mathcal{I}(e, \Gamma)$ attempts concrete evaluation of the expression e in the enclosing external Γ_{ext}. If it returns some concrete object ⟨const...⟩, the analysis returns ({t}, {t = ⟨const...⟩}). We employ the following heuristic. For Identifier and Attribute expressions (i.e., simple expressions), we first attempt resolution in the abstract environment: first Γ then Γ_0. If it fails, we attempt concrete evaluation. For all other expressions (i.e., complex expressions), we first attempt concrete evaluation in Γ_{ext}, and if it fails we proceed with interpretation. Below we describe interpretation (i.e., 3-address code generation).

3.2.7 Interpretation of statements and expressions. The definition of the interpretation function is presented in Figure 4. Below we highlight the most interesting points.

Statements. Consider interpretation of assignment $x = e$. If the variable x appears in a module initializer, we retrieve the analysis variable from Γ_0 (imports also create implicit global assignments). Otherwise, we only augment the local environment with a fresh variable if the variable x is not in the current environment. We target flow-insensitive points-to analysis, and thus, a Python sequence `x = 1; x = "a"` gives rise to 3-address code sequence t1 = 1; t1 = "a" and fails to distinguish that x is an integer at the first assignment and a string at the second. This above code makes explicit that we do not handle `global x` soundly. `global` defaults to *Other*, and does not create meaningful 3-address code, an assignment to a global x results in a local assignment.

The interpretation of a loop statement for x in e: s reduces to a sequence of assignment $x = e$ followed by s. The assignment binds identifier x before descending into the interpretation of s.

If a function definition occurs in a module initializer, then there is an entry for $M.f$ in Γ_0. Otherwise, i.e., if this function is nested into another function, we augment the local environment with f and return the augmented environment. Function definition gives rise to a "new" statement, assigning the abstract `meta-func` object to t. Class definitions have no effect during interpretation. Module-level class definitions are processed during class hierarchy analysis.

For uninterpreted statements, the algorithm descends into each sub-statement and extracts the corresponding 3-address code. These statements do not "glue" components according to the semantics of the statement. However recursive descent processes all nested assignments and calls; it appropriately augments the environment and generates 3-address code that captures value flow.

Expressions. The interpretation of a variable first searches the local environment (i.e., the enclosing function), and then the global environment if the first lookup failed. We ignore static reference environments for nested functions, which is unsound in general. A function value may flow to arbitrary points of the program and it is interpreted into 3-address code when it is called at some point; however, interpretation happens in the empty environment rather than the actual static reference environment and references coming from enclosing scopes evaluate to empty sets. Similarly, for an attribute access, if the lookup in Γ yields no result, the analysis maps $e.f$ to a module-level-construct identifier, i.e., $M.C$, $M.f$ or $M.x$, and searches Γ_0 to retrieve the corresponding analysis variable t (the step is not shown in the figure). Subscript expressions treat [] as a special field, which is the standard in points-to analysis.

To interpret a list, we create a new list object and generate subscript assignments to populate the list. Tuple, set, and dictionary are analogous. Remaining expressions (list and dictionary comprehensions) and statements (sequence, complex assignment, return and for) is as expected.

For uninterpreted expressions we simply returns the union resulting from the interpretation of each sub-expression.

Import. Finally, to interpret imports in module initializers (last rule of Figure 4), we first find the enclosing module M' of imported construct x', and then look up for the representative analysis variables t1 and t2 corresponding to the imported construct $M'.x'$ and the alias x in the current module M. The statement t2 = t1 propagates the value (e.g., a function definition, a class definition) from module M' to M.

3.3 Constraint Resolution

As mentioned earlier, the analysis maintains abstract objects and concrete objects. Abstract objects are explicitly grouped into *data objects*, *function objects*, and *class object*:

(data, ⟨class C(...): ...⟩)	*an abstract data object*
(meta-func, ⟨def f(...): ...⟩)	*an abstract function object*
(meta-cls, ⟨class C(...): ...⟩)	*an abstract class object*
(const, ..., ...)	*a concrete object*

The 3-address statements are as specified in Figure 2. These statements induce constraints that populate a points-to graph Pt. The nodes in the points-to graph are analysis variables as well as objects o of the above kinds. The edges represent the points-to relation. E.g., there could be an edge from variable t to an object o, and this is denoted as $\{o\} \subseteq Pt(t)$ or equivalently as $t \longrightarrow o$. There could be a field edge indicating that field f of o_1 points to o_2 and this is denoted as $\{o_2\} \subseteq Pt(o_1.f)$ or equivalently as $o_1 \xrightarrow{f} o_2$.

The rules for new assignment, copy propagation and field write are largely standard (except for their returns) and we elide them from the presentation. We elaborate on the rules for field read $t_1 = t_2.f$ and function call $t_1 = t_2(t_3)$ as they illustrate Python-specific semantics and concrete evaluation.

solve for $t_1 = t_2.f$ *in* ⟨def f'(...): ...⟩ *with* Γ_{ext}:
for $o \in Pt(t_2)$
  case o **of**
    (data, ⟨class C(...): ...⟩) $\longrightarrow$
      ⟨def f(self, p): ...⟩ $\longleftarrow H[(\langle$class C(...): ...$\rangle, f)]$
      $Pt(t_1) \longleftarrow Pt(t_1) + \{$(meta-func, ⟨def $f(o, p)$: ...⟩)$\}$
    (meta-cls, ⟨class C(...): ...⟩) $\longrightarrow$
      ⟨def f(self, p): ...⟩ $\longleftarrow H[(\langle$class C(...): ...$\rangle, f)]$
      $Pt(t_1) \longleftarrow Pt(t_1) + \{$(meta-func, ⟨def f(self, p): ...⟩)$\}$
    (const, ...) $\longrightarrow Pt(t_1) \longleftarrow Pt(t_1) + \{eval(o.f, \Gamma_{ext})\}$
  $Pt(t_1) \longleftarrow Pt(t_1) + Pt(o.f)$
return {⟨def f'(...): ...⟩} if $Pt(t_1)$ changed else {}

The rule examines each object in the points-to set of receiver variable t_1 and does case-by-case analysis on the object type. E.g., if it is an abstract data object of some user-defined class, the analysis searches the class hierarchy (MRO) to determine the function referenced by $o.f$, forms the closure by binding *self* to the receiver object o and adds the closure object to the points-to set of left-hand-side t_1. If the object is a concrete object, the analysis evaluates the field access returning a new concrete object and adding it to the points-to set of t_1.

The last line returns the enclosing function f' to the worklist if there is a change to the points-to set of t_1, as the change may trigger changes to other points-to sets in f'.

```
I(pass, Γ)              = return (Γ, {})

I(x = e, Γ)             = (R, S) ← I(e, Γ)
                          if scope is M.module_init :
                            t ← lookup(M.x, Γ0)
                            return (Γ, S ∪ {t = t_e | t_e ∈ R})
                          if x ∈ Γ :
                            t ← lookup(x, Γ)
                            return (Γ, S ∪ {t = t_e | t_e ∈ R})
                          else:
                            t ← fresh variable
                            Γ′ ← [(x, t)] + Γ
                            return (Γ′, S ∪ {t = t_e | t_e ∈ R})

I(s1 ; s2, Γ)           = (Γ1, S1) ← I(s1, Γ)
                          (Γ2, S2) ← I(s2, Γ1)
                          return (Γ2, S1 ∪ S2)

I(for x in e: s, Γ)     = I(x = e ; s, Γ)

I(def f(...): ..., Γ)   = if scope is M.module_init :
                            t ← lookup(M.f, Γ0)
                            return (Γ, {t = (meta-func⟨def f(...): ...⟩)})
                          else:
                            t ← fresh variable
                            Γ′ ← [(f, t)] + Γ
                            return (Γ′, {t = (meta-func⟨def f(...): ...⟩)})

I(class C(...): ..., Γ) = return (Γ, {})

I(Other (s1, ..., sn), Γ) = (Γ1, S1) ← I(e1, Γ)
                            ...
                            (Γn, Sn) ← I(en, Γn−1)
                            return (Γn, S1 ∪ ... ∪ Sn)
```

```
I(x, Γ)                 = if x ∈ Γ: return ({lookup(x, Γ)}, {})
                          if M.x ∈ Γ0: return ({lookup(M.x, Γ0)}, {})
                          else: return ({}, {})

I(e.f, Γ)               = t ← fresh variable
                          (V, S) ← I(e, Γ)
                          return ({t}, S ∪ {t = t_e.f | t_e ∈ V})

I(e1[e2], Γ)            = t ← fresh variable
                          (V1, S1) ← I(e1, Γ)
                          (V2, S2) ← I(e2, Γ)
                          return ({t}, S1 ∪ S2 ∪ {t = t1[] | t1 ∈ V1})

I(e1(e2), Γ)            = t ← fresh variable
                          (V1, S1) ← I(e1, Γ)
                          (V2, S2) ← I(e2, Γ)
                          return ({t}, S1 ∪ S2 ∪ {t = t1(t2) | t1 ∈ V1, t2 ∈ V2})

I([e], Γ)               = t ← fresh variable
                          (V, S) ← I(e, Γ)
                          S′ ← {t = (data⟨class list⟩)} ∪ {t[] = t_e | t_e ∈ V}
                          return ({t}, S ∪ S′)

I(Other (e1, ..., en), Γ) = (V1, S1) ← I(e1, Γ)
                            ...
                            (Vn, Sn) ← I(en, Γ)
                            return (V1 ∪ ... ∪ Vn, S1 ∪ ... ∪ Sn)

I(from p import x′ as x, []) = M′ ← find module of x′
                               t1 ← lookup(M′.x′, Γ0)
                               t2 ← lookup(M.x, Γ0)
                               return ({}, {t2 = t1})
```

Figure 4: From Python to 3-address-code. Given an environment Γ, the interpretation function for a statement $\mathcal{I}(s, \Gamma) = (\Gamma', S)$ (left) returns an updated environment Γ' and the 3-address code S. The interpretation function for an expression $\mathcal{I}(e, \Gamma) = (V, S)$ (right) returns a set of analysis variables V and the 3-address code S. M is the enclosing module, and Γ_0 is the global environment.

```
solve for t1 = t2(t3) in ⟨def f′(...): ...⟩ with Γ_ext:
for o ∈ Pt(t2)
  if o is an abstract object
    case o of
    (data, ⟨class C(...): ...⟩) → # call on data/instance
      callee ← H[(⟨class C(...): ...⟩, '__call__')]
      rcv ← {o}
    (meta-cls, ⟨class C(...): ...⟩) → # constructor call
      callee ← H[(⟨class C(...): ...⟩, '__init__')]
      rcv ← {(data, ⟨class C(...): ...⟩)} # new object
    (meta-func, ⟨def f(o′, p): s⟩) → # closure call
      callee ← ⟨def f(self, p): s⟩
      rcv ← {o′}
    (meta-func, ⟨def f(p): s⟩) →
      callee ← ⟨def f(p): s⟩ # the function def
      rcv ← None
    if ⟨def f(p): s⟩ ∉ Φ # callee is not interpreted
      # env. includes self when f is an instance function
      t ← fresh variable
      Φ[⟨def f(p): s⟩] ← I(s, [(p, t)])
    if rcv ≠ None # there is a receiver
      # retrieve analysis variable corresponding to self:
      t4 ← Φ[⟨def f(self, p): s⟩][0][self]
      Pt(t4) ← Pt(t4) + rcv # receiver to self
    t5 ← Φ[⟨def f(p): s⟩][0][p]
    Pt(t5) ← Pt(t5) + Pt(t3) # actual to formal
    t6 ← Φ[⟨def f(p): s⟩][0][f_ret]
    Pt(t1) ← Pt(t1) + Pt(t6) # ret var to lhs of call
  else # o is a concrete object
    for o1 in Pt(t3)
      if o1 is a concrete object
        Pt(t1) ← Pt(t1) + {eval(o(o1), Γ_ext)}
return {⟨def f(...): ...⟩, ⟨def f′(...): ...⟩} if change else {}
```

There are two cases at the top level, an abstract object as function value and a concrete object as function value. In the case of an abstract object, we do case-by-case analysis. If o is a data object, it queries the hierarchy to retrieve the corresponding __call__ function — this is the function that is being called. Otherwise, if it is a meta class object, this leads to the retrieval of the constructor. Finally if it is a meta function, there are two cases: the function is a closure where self is already bound to a receiver, and the function is just a value with a null reference environment.

Once the analysis identifies the function to be called at this site, it checks if an interpretation of this function into 3-address code already exists. If it does not we interpret it. Notably, we interpret the AST of the function in the empty environment (i.e., only parameters are bound). This means that a first-class function does not carry its static reference environment and the analysis introduces unsoundness. This is an engineering choice: while it is possible to extend the analysis with such bindings, this will complicate code significantly, while in practice it will have limited impact. A notable departure from standard Java analysis is that there is no explicit new A() site. Different meta class objects may flow to receivers of calls accounting for data object creation (but note that number of meta class objects is bounded and thus number of data objects instantiated at the call is finite).

Once the calee function is interpreted the analysis propagates points-to sets from actual arguments t_3 to formal parameters p and return values to the left-hand-side of the call t_1.

In case of a concrete receiver, analysis searches for concrete arguments and if it finds them executes the function.

4 RESULTS

We evaluate our Andersen-style points-to analysis, PoTo, on type inference; however, we note it has a wide variety of applications and we envision many different clients. The analysis can be run on any Python package. It starts at a provided entry function and computes a points-to graph containing information on reachable variables and their inferred types. To thoroughly analyze a library package, a set of entry functions are needed. We follow DLInfer, a neural type inference for Python, and use the same 10 Python packages from their experiment available with DLInfer's artifact. The 10 packages range in size from 3,556 LOC to 285,515 LOC (see Table 1). These packages contain rich test cases which suit our need of diverse entry points. We use each function in a package's test directory as an entry point. For five of the packages (cerberus, mtgjson, pygal, sc2, and zfsp), we additionally create custom entry functions targeting remaining unreachable public functions. For the other five packages (anaconda, ansible, bokeh, invoke, and wemake_python_styleguide), we only use default test suites.

To better target unreachable methods, we enhance the analysis. We achieve this by performing a shallow analysis that collects built-in type information and type annotations from assignment and return statements. For example, consider an assignment with a built-in type: `rules = set(schema.get(field, ()))`. The shallow analysis infers that `rules` can be of type `set`. This has impact when the method is unreachable from PoTo's entry points, as it creates a key and infers a type for the `rules` local variable. The final results, called PoTo+, are stored as a dictionary of *keys* to their inferred types. A *key* is a tuple of (module name, function name, variable name), describing the variable and its scoping information. Keys largely correspond to local variables (including arguments and returns) in a package and are an abstraction for flow-insensitive analysis, the target of our work. The remainder of this section uses the terms keys and variables interchangeably.

We compare the results of PoTo+ against four other type inference techniques. Three of these are based on the recent neural type inference work DLInfer [28]: DL-ST, DL-DY, DL-ML. We make use of the result files available with DLInfer's artifact [27]. DL-ST is their ground truth information, which is a combination of running the Pysonar2 static tool and extracting type information [25]. DL-DY is a set of dynamic type information obtained from executing the test suites. This dynamic set contains only variables whose type can be collected only this way, meaning that this is the set difference of the actual dynamic run and DL-ST set [28]. Lastly, DL-ML is the result of DLInfer's machine-learning approach. We aggregate each DLInfer result in the same way as our analysis, which is a dictionary of keys to their types.

We choose DLInfer for several reasons: (1) DLInfer is recent work in a top conference, (2) it compares with several state-of-the-art deep-learning techniques: Type4Py [17], Typilus [1], PYInfer [6], and DeepTyper [10], (3) DLInfer infers types for local variables, not only parameters and returns, and (4) DLInfer's artifact [27] includes full Python packages along with analysis results allowing for a comparison over the same code base.

In addition to DLInfer, we also compare our result to Pytype, a prominent static type checking and type inferece tool [8]. To get type information for all variables, we instrument the package by inserting Pytype's command `reveal_type(var)` for each local variable at the end of a function, and run Pytype on each file in the package directory. The types are then collected and combined to be the inferred result of Pytype. This process takes time to complete but only needs to be done once. We note that this is a departure from standard use of Pytype as baseline for type inference work, which uses Pytype's result on parameters and returns only (e.g. [18]); Pytype is able to infer types for local variables as well and we make use of this in our comparison.

Our evaluation considers 4 research questions:

- RQ1: How high is the coverage of PoTo+ compared to other type inference techniques?
- RQ2: To what extent are the types from PoTo+ equivalent to those from other techniques?
- RQ3: In cases where the types from PoTo+ do not match those from other techniques, which one is correct?
- RQ4: Does the time to run PoTo scale well and how does it compare to Pytype?

Summary of findings. To answer RQ1, we measure the percentage of total keys in a package for which our analysis reports types against the percentage of total keys for which the four other type inference techniques report types (more detail on methodology in Section 4.1). Our analysis collects types for a *larger percentage of total keys* compared to the four other techniques. To answer RQ2, we compare our inferred types to those inferred by each of the four other techniques, measuring the equivalence in term of total match, partial match, and mismatch (more detail in Section 4.2). Our inferred types *largely match with Pytype's*. While there some match with DLInfer, there is disagreement in many keys.

To answer RQ3, we inspect a sample of mismatches according to the result from RQ2 for each pair comparisons: PoTo+ vs. Pytype, PoTo+ vs. DL-*. We found that in the few cases where there is a mismatch with Pytype, Pytype is correct in all cases. A mismatch with DL-* is, nearly always, a correct result by PoTo, but an incorrect result by DL-*. The conclusion from RQ1-RQ3 is that *traditional techniques outperform a state-of-the-art neural technique* for the task of type inference. Lastly, for RQ4, we compare the total time to run PoTo (with dozens of entry functions for the smaller packages

Table 1: Statistic of the dataset.

Package	Total number (in test dir)		Total keys
	Files	LOC	
cerberus	45 (32)	6,694 (3,011)	966
mtgjson	54 (2)	6,912 (58)	1,378
pygal	78 (24)	13,780 (3,208)	2,439
sc2	69 (6)	11,205 (603)	5,970
zsfp	54 (7)	3,556 (207)	1,345
anaconda	370 (9)	90,207 (587)	21,183
ansible	1,445 (961)	285,515 (174,296)	22,346
bokeh	1,133 (280)	131,931 (43,316)	14,978
invoke	133 (65)	26,159 (9,878)	3,474
wemake	403 (291)	55,841 (32,798)	3,184

and thousands for the larger ones) to the time to run Pytype to collect reveal-type information. On all but one package, ansible, PoTo outperforms Pytype significantly.

4.1 Coverage (RQ1)

Table 1 shows the statistic of all 10 packages. The number of files and lines of code are presented as overall numbers with ones in test directories in parentheses. We are interested in inferring types for the core package and exclude test files from our reports. The total keys include all variables, function arguments, and function return types. They serve as an upper limit of possible variables (or keys) for each package.

Figure 5 shows the percentages of non-empty keys to the total keys for each package. The notion of empty keys means variables that our analysis or the other techniques know the existence of, but does not have information of their types, hence their sets of inferred types are shown as Empty. In the case of Pytype, a key is designated as Empty if its inferred type is the trivial `Any` type. DL-ST and DL-DY do not have any empty keys by design. They are ground truth and dynamic information of DLInfer. The numbers above each bar are the numbers of non-empty keys. For the five packages (cerberus, mtgjson, pygal, sc2, and zfsp) where we add custom entry functions, PoTo+ covers more non-empty keys than other techniques, followed closely by Pytype. For the remaining packages where we only use default test suites, we have slightly worse coverage than Pytype on anaconda and invoke, reflecting worse test coverage by the underlying test suites. PoTo+ still has the highest average coverage percentage.

4.2 Equivalence (RQ2)

Next, we measure the similarity of inferred types. For each variable in a package, our analysis and the other type inference techniques can either have an information on this variable, and the information can be the set (i.e. union) of its inferred types or an empty set. We focus on keys where both our results and the compared techniques are non-empty, meaning that we and they infer some types.

Comparison is trivial for built-in types. For built-in containers such as `dict`, `list`, `set`, and `tuple`, we compare only the top-level part and deem that they match if they are the same container types. The main reason for this shallow comparison is to facilitate processing and comparison as each type inference technique infers and reports types in different forms. For example, DLInfer reports only the type of a container, e.g., `dict`. Pytype reports parametric information, e.g., `Dict[str, int]`, but not always, while PoTo+'s inferred types come from abstract and concrete objects, e.g., `{'rename_handler': <class 'int'>}`. PoTo can collect parametric information, but it requires significant processing and raises issues on reporting types for polymorphic containers.

Matching is automatic but some comparisons require manual verification because of rendering of PoTo concrete objects. For example, PoTo+'s `1970-01-01` matches with DL-ST's `datetime.date` type. Another example is a match between PoTo+'s `<function <lambda> at 0x109297520>` and Pytype's `Callable[[Any],Any]`.

We are interested in 3 groups of equivalence: total match, partial match, and mismatch. Figure 6 shows this as an average across the 10 Python packages. On all Python packages, PoTo+ share the most non-empty keys with Pytype, and has high numbers of total matching. DL-ST and DL-ML have some matching and partial matching with our analysis, but also contain many keys that are mismatches. This discrepancy is discussed in Section 4.3. Note that for the sc2 package, almost all common keys between PoTo+ and DL-ML are mismatches. They are simple assignments of class attributes in /sc2/ids/ directory, e.g. `NULL = 0`, `RADAR25 = 1`, `TAUNTB = 2`. Our analysis, Pytype, and DL-DY correctly infer the types as integer, but DL-ML labels all of them as `num` which is incorrect as it is not a type. Lastly, DL-DY has low coverage of types information, and most of them are a total match with our analysis.

4.3 Correctness (RQ3)

To carry out the comparison we manually examine a sample of 10 "not-match" keys for each package and each pair of comparisons, i.e., PoTo+ vs. Pytype, PoTo+ vs. DL-ST, PoTo+ vs. DL-DY, and PoTo+ vs. DL-ML. In cases where there are fewer than 10 non-match keys, we exhaustively examine all of them, (e.g., there are only 8 non-matches between PoTo+ and Pytype for pygal, so there are 8 instead of 10 keys for pygal). There are only 18 total non-matches keys for PoTo+ vs. DL-DY. For the remaining 3 techniques, the total is slightly under 300 samples. Results are shown in Figure 7.

PoTo+ vs. Pytype. Comparison with Pytype shows that a mismatch usually means that PoTo+ is incorrect while Pytype is correct. Of the 86 pairs we examined, PoTo+ is correct 45 times, while Pytype is correct 86 times. The numbers give the impression that PyType is significantly more accurate than PoTo+. However, looking at the overall results in Figure 5 and Figure 6, one sees that Pytype and PoTo+ report essentially the same types. Of the 36,991 variables for which Pytype reports a meaningful type, 29,252 (nearly 80%) are covered by PoTo+ as well. Of those 29,252, 26,457 (over 90%) have the same type in Pytype and in PoTo+ and 2,506 (about 9%) are a partial match between Pytype and PoTo+. Figure 7 zooms in on the remaining mismatched 289 keys, which is less than 1% of all variables. We find the results highly reassuring of PoTo's correctness given that Pytype is a mature and widely used tool. Many of the 289 mismatches will be eliminated by extending PoTo with handling of additional AST constructs as we explain below.

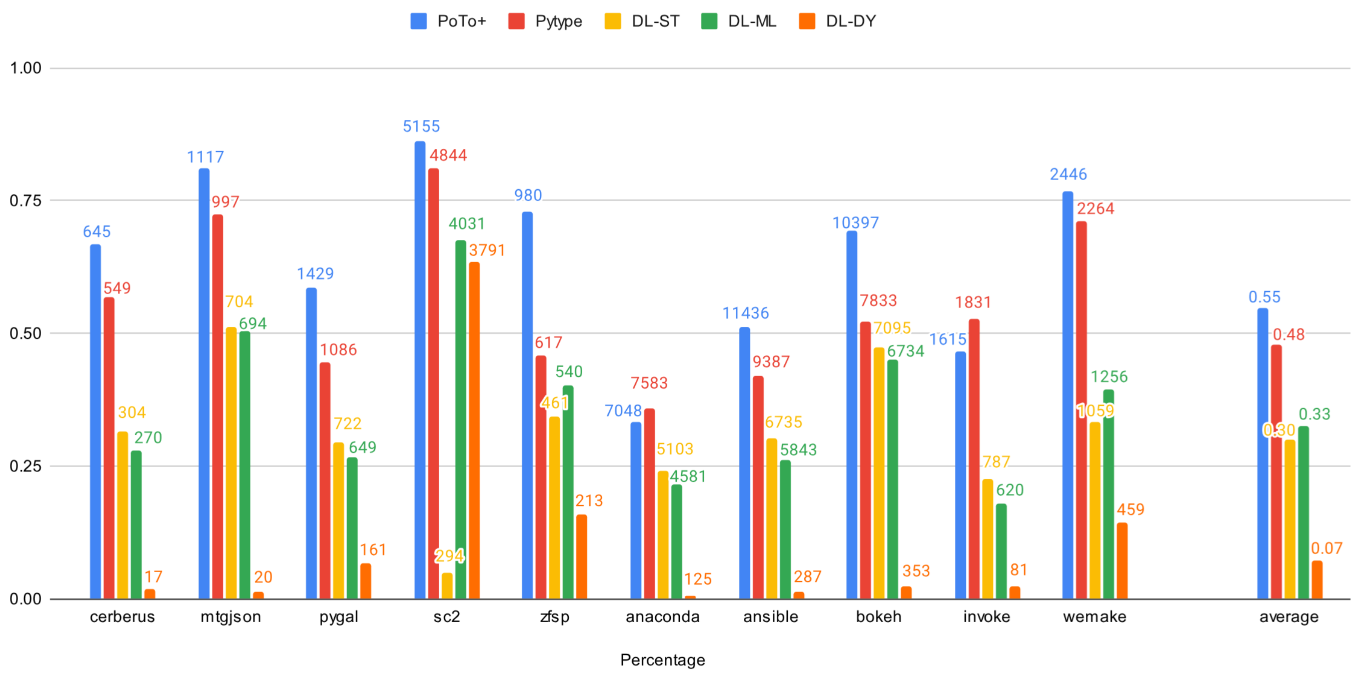

Figure 5: Coverage percentages of non-empty keys to total keys (RQ1).

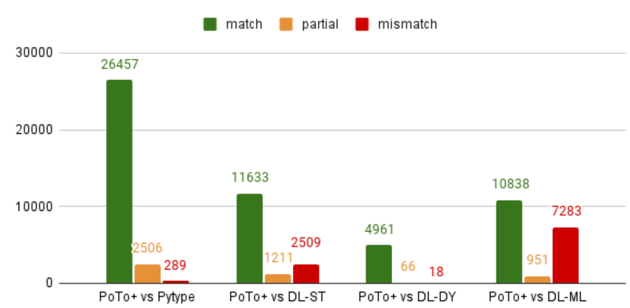

Figure 6: Equivalence comparison between PoTo+ and other type inference techniques (RQ2). Numbers are average across all 10 packages.

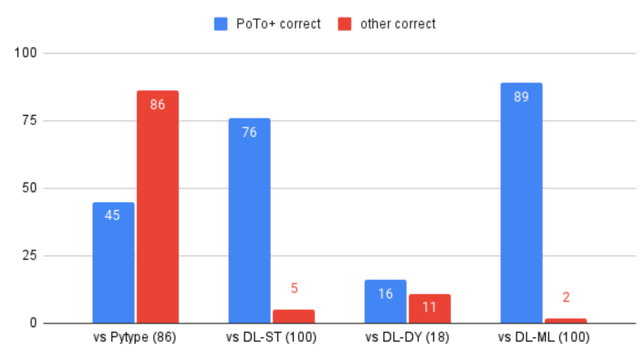

Figure 7: Correctness comparison between PoTo+ and other techniques (RQ3). Numbers in parentheses are # of samples.

Looking more closely, Pytype handles a larger set of Python features precisely, while PoTo defaults to Other, thus polluting points-to sets. For example, PoTo does handle list and dictionary comprehensions precisely, but defaults to Other on set comprehensions. Consider the example:

```
rampPoints = {p for p in rampDict if rampDict[p]}
```

Recall that handling of Other propagates points-to sets of `p`, `rampDict` and `rampDict[p]` into `rampPoints`. This leads to PoTo+ reporting type `[dict, bool]` as `p`'s set is empty and `rampDict`'s set contains a single dictionary object of `Point` object keys, and bool values (it is straightforward to add handling of set comprehensions and other features to PoTo to improve matching and we will add it in the future).

For the majority of cases where both are correct, PoTo+ reports a concrete type while Pytype reports a type parameter. For example, PoTo+ reports correctly `[dict, None]`, i.e., an optional dictionary for the return type of `_normalize_purge_unknown` in the cerberus package; while Pytype reports type variable `[_T0]` and this is correct with respect to Pytype's type system which allows for polymorphic functions.

PoTo+ vs. DL-ML, DL-ST and DL-DY. Of the 100 pairs we examine for PoTo+ vs. DL-ML, PoTo+ is correct 89 times, while DL-ML is correct 2 times. We also note that we mark PoTo+ incorrect conservatively — essentially, when the result is partially correct but not sound and not complete, we mark it incorrect. One common source of incorrect result for DL-ML was the `num` types mentioned

Table 2: Running times of PoTo and Pytype (RQ4).

Package	PoTo	Pytype
cerberus	51s	4m22s
mtgjson	1m39s	15m39s
pygal	1m48s	1h00m17s
sc2	52s	40m29s
zsfp	11s	7m28s
anaconda	1m59s	1h21m40s
ansible	6h23m07s	6h14m59s
bokeh	1h41m16s	10h15m41s
invoke	1m32s	20m45s
wemake	3m25s	9m17s

earlier. Another source is usage of the function name instead of the function's return type at call assignments. Consider the following example from package pygal: `background = lighten('#e6e7e9',7)`. DL-ML reports type `[lighten]` for `background`, while PoTo+ correctly reports `[str, tuple]`. Yet another source of incorrect results is over-reliance on `dict` types. For example, in the wemake package: `AnyFunctionDef=Union[ast.FunctionDef,ast.AsyncFunctionDef]`, PoTo+ correctly infers type `[typing.Union[...]]` for `AnyFunctionDef` (via concrete evaluation in this case). DL-ML infers `[dict]`.

Of the 100 samples we examine for PoTo+ vs. DL-ST, PoTo+ is correct 84 time and DL-ST is correct 5 times. There are no `num` types, as they are correctly assigned `int`; however, we observe similar patterns of function name instead of return type, and over-reliance on `dict`.

There are only 18 total mismatches for PoTo+ vs. DL-DY; 8 from ansible and 10 from bokeh. PoTo+ is correct 16 times and DL-DY is correct 11 times. Most cases are from accessing a dictionary or calling a function such as `children = kwargs.get('children')` or `typ = type(obj)`. On 5 occasions, DL-DY infers types that appear wrong such as `type`.

4.4 Scalability of PoTo (RQ4)

Table 2 show the running times of PoTo (this is the total time to execute thousands of entry functions) and of Pytype. We run on a commodity Mac book Pro with 2.4 GHz 8-Core Intel Core i9 and 32 GB of Memory (one of our development machines). The "+" phase (type inference) is instantaneous and type aggregation and processing are negligible. We do not include these in the timing. In both cases, execution is IO-dominated, as PoTo writes points-to results into pkl files and Pytype prints error messages (reveal-type reveals types as a special error message).

PoTo runs in 1–3 minutes for all but the two largest packages, bokeh and ansible. Pytype is significantly more expensive ranging between 4 and 81 minutes on those packages. We measured that without the reveal-type instrumentation Pytype runs 30% faster; thus, its underlying static analysis is expensive and PoTo still outperforms Pytype. PoTo outperforms Pytype on the bokeh package significantly, while it does run slower in total time on ansible. This is because ansible has nearly 500 test file (we filtered out ones that do not reference ansible packages from the 961 original ones to speed up testing) and many hit the same bottleneck of ansible code in the points-to analysis.

5 THREATS TO VALIDITY

Section 4.3 discusses correctness comparison that depends on limited samples out of thousands of mismatches. To mitigate this, we collect all 18 mismatches against DL-DY, plus 10 samples per packages for all packages across 3 other techniques, resulting in total of 300 hand-labeled examples with broad coverage.

The analysis relies on unit tests for entry points, thus presuming the existence of test suites and good test coverage of the test suites. To increase coverage, we added custom entry-points for 5 of the packages; notably, coverage remains robust even for those large packages where we used only the existing test suites.

Lastly, PoTo is a hybrid analysis that alternates between concrete and abstract evaluation, and it employs semantic choices to deal with Python's complexity. This makes the analysis unsound by design, but it is the typical kind of trade-off made by most real-world static analysis [15].

6 RELATED WORK

This section discusses prior work related to each of the three contributions stated at the end of Section 1.

Andersen-style points-to analysis for Python. At its core, PoTo is an implementation of Andersen's points-to analysis [2], but unlike the original, it works for Python and is hybridized with concrete evaluation. The only other points-to analysis for Python we have found is in Scalpel [14]; however, Scalpel's analysis is not based on Andersen's, does not use concrete evaluation, and the paper lacks empirical results. Few static analyses have been shown to work on real-world Python programs, including PyCG [21] (which finds call graphs) and Tree-sitter [5] (which is limited to syntactic queries) [5]. Neither PyCG nor Tree-sitter does points-to analysis, nor do they use concrete evaluation.

Hybridization weaving concrete and abstract evaluation. PoTo uses concrete evaluation to solve the problem of analyzing Python programs that use external libraries. Two other works hybridize abstract (i.e. static) with concrete (i.e. dynamic) analysis for Python: PyCT [4] (which does concolic testing) and Rak-amnouykit et al.'s analysis [20] (which finds weakest preconditions). Neither of these two is based on points-to analysis, and neither of them has been used for type inference. Instead of hybridizing static analysis with concrete evaluation, several works hybridize static analysis with machine-learning (ML). Xu et al. present a static type inference for Python augmented with ML for guessing types based on variable names [26]. Typilus uses static analysis to build a Python program dependency graph, then uses a graph neural network for type inference [1]. TypeWriter performs deep-learning (DL) type inference, then uses a static type checker to repair hallucinations [19]. Type4Py [17], HiTyper [18], and DLInfer [28] are primarly DL type inferences for Python, assisted by simple static analyses. In contrast, PoTo is a static points-to analysis for Python hybridized with concrete evaluation, not with deep learning.

The above discussion focused on hybridization in program analysis for Python. However, hybridization is a longstanding program analysis technique that has been studied and applied for decades.

Notable recent work includes Tolman and Grossman's Concerto framework [23] applied on a Java subset, and Laursen et al.'s hybrid analysis for JavaScript [13] which improves accuracy of JavaScript call graphs. In contrast to these works, we explore hybrid analysis for Python, which we believe is an important future direction in program analysis for Python. We specifically target points-to analysis for Python.

Type inference for Python. PYInfer [6] and DeepTyper [10] use deep learning for Python type inference, and, as discussed in the previous paragraph, several other works combine deep learning with simple static analysis [1, 17–19, 26, 28]. This paper empirically compares PoTo+ against the latest of those, DLInfer [28], chosen because it compares with several earlier works and its artifact [27] has points-to sets for 10 real-world Python programs. A handful of other works use static analysis for Python type inference, including Pytype [8], as well as papers by Maia et al. [16], Fritz and Hage [7], and Hassan et al. [9]. Unlike PoTo+, none of these use points-to analysis nor concrete evaluation. This paper empirically compares PoTo+ against Pytype [8], chosen because it is widely used in practice and, like PoTo+, handles real-world Python programs.

7 CONCLUSIONS

This paper presents PoTo, the first Andersen-style points-to analysis for Python. PoTo works on real-world Python programs, which use dynamic features as well as external packages for which source code is often missing (and which often involve non-Python code). To handle external packages, PoTo introduces a novel hybridization of Andersen's static analysis with dynamic concrete evaluation. Points-to analysis can (among other clients) be applied to type inference, which is becoming more and more popular for Python thanks to rising adoption of its gradual type system. Therefore, this paper presents PoTo+, a type inference built upon PoTo. While several recent papers explore deep learning for Python type inference, our results indicate that (at least as of now) static analysis solves this problem with superior coverage and correctness.

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