TypeWriter: Neural Type Prediction with Search-based Validation

Michael Pradel
University of Stuttgart
michael@binaervarianz.de

Jason Liu
jasonliu@fb.com
Facebook

Georgios Gousios†
Delft University of Technology
g.gousios@tudelft.nl

Satish Chandra
satch@fb.com
Facebook

ABSTRACT
Maintaining large code bases written in dynamically typed languages, such as JavaScript or Python, can be challenging: simple data compatibility errors proliferate, IDE support is lacking and APIs are harder to comprehend. Recent work attempts to address those issues through either static analysis or probabilistic type inference. Unfortunately, static type inference for dynamic languages is inherently limited, while probabilistic approaches suffer from imprecision. This paper presents TypeWriter, the first combination of probabilistic prediction with search-based refinement of predicted types. TypeWriter’s predictor learns to infer the return and argument types for functions from partially annotated code bases by combining the natural language properties of code with programming-language-level information. To validate predicted types, TypeWriter invokes a gradual type checker with different combinations of the predicted types, while navigating the space of possible type combinations in a feedback-directed manner.

We implement the TypeWriter approach for Python and evaluate it on two code corpora: a multi-million line code base at Facebook and a collection of 500 popular open-source projects. We show that TypeWriter’s type predictor achieves a precision of 64% (91%) and a recall of 52% (68%) in the top-1 (top-5) predictions, and demonstrate that usage contexts are a helpful addition to neural type predictors. By combining predictions with search-based validation, TypeWriter can fully annotate between 42% to 64% of the files in a randomly selected corpus, while ensuring type correctness. A comparison with a static type inference tool shows that TypeWriter adds many more non-trivial types. Overall, TypeWriter provides developers with an effective way to help with the transition to fully type-annotated code.

1 INTRODUCTION
Dynamically typed programming languages, such as Python and JavaScript, have become extremely popular, and large portions of newly written code are in one of these languages. While the lack of static type annotations enables fast prototyping, it often leads to problems when projects grow. Examples include type errors that remain unnoticed for a long time [8], suboptimal IDE support, and difficult to understand APIs [19]. To solve these problems, in recent years, many dynamic languages obtained support for type annotations, which enable programmers to specify types in a fashion similar to a statically typed language. Type annotations are usually ignored at runtime; nevertheless, they serve both as hints for developers using external APIs and as inputs to gradual type checkers that ensure that specific programming errors cannot occur. To cope with legacy code bases, type annotations can be introduced gradually; in such cases, the type checker will check only code that is annotated.

As manually annotating code is a time consuming and error-prone process [21], developers must resort to automated methods. One way to address the lack of type annotations is type inference via traditional static analysis. Unfortunately, dynamic features, such as heterogeneous arrays, polymorphic variables, dynamic code evaluation, and monkey patching make static type inference a hard problem for popular dynamic languages, such as Python or JavaScript [6]. Static type inference tools typically handle these challenges by inferring a type only if it is certain or very likely (under some assumptions), which significantly limits the number of types that can be soundly inferred.

Motivated by the inherent difficulties of giving definitive answers via static analysis, several probabilistic techniques for predicting types have been proposed. A popular direction is to exploit the existence of already annotated code as training data to train machine learning models that then predict types in not yet annotated code. Several approaches predict the type of a code entity, e.g., a variable or a function, from the code contexts in which this entity occurs [13, 23]. Other approaches exploit natural language information embedded in source code, e.g., variable names or comments, as a valuable source of informal type hints [18, 30].

While existing approaches for predicting types are effective in some scenarios, they suffer from imprecision and combinatorial explosion. Probabilistic type predictors suggest one or more likely types for each missing annotation, but they leave the task of deciding which of these suggestions are correct to the developer. In particular, existing predictors do not help in choosing a type-correct combination of type annotations across multiple entities. A naive approach would be to let a developer or a tool choose from all combinations of the predicted types. Unfortunately, this approach does not scale to larger code examples, because the number of type combinations to consider is exponential in the number of not yet annotated code entities.

This paper presents TypeWriter, a combination of learning-based, probabilistic type prediction and a feedback-directed, search-based
Figure 1: Example of search for type-correct predicted types.

validation of predicted types. The approach addresses the imprecision problem based on the insight that a gradual type checker can pinpoint contradictory type annotations, which guides the selection of suitable types from the set of predicted types. To make the search for a consistent set of types tractable, we formulate the problem as a combinatorial search and present a search strategy that finds type-correct type annotations efficiently. TypeWriter makes use of the variety of type hints present in code through a novel neural architecture that exploits both natural language, in the form of identifier names and code comments, similar to prior work [18], and also programming context, in the form of usage sequences.

To illustrate the approach, consider the two to-be-typed functions in Figure 1. Given this code, the neural type model of TypeWriter predicts a ranked list of likely types for each argument type and return type, as indicated by the comments. TypeWriter starts by adding the top-ranked predictions as type annotations, which introduces a type error about an incorrect return type of find_match, though. Based on this feedback, the search tries to change the return type of find_match to the second-best suggestion, Optional[str]. Unfortunately, this combination of added types leads to another type error because the return type is inconsistent with the argument key being of type int. The search again refines the type annotations by trying to use the second-best suggestion, str, for the argument key. Because the resulting set of type annotations is type-correct according to the type checker, TypeWriter adds these types to the code.

We implement TypeWriter for Python and apply it on two large code bases: a multi-million line code base at Facebook that powers applications used by billions of people, and a corpus of popular open-source projects. We show that the neural model predicts individual types with a precision of 64% (85%, 91%) and a recall of 52% (64%, 68%) within the top-1 (top-3, top-5) predictions, which outperforms a recent, closely related approach [18] by 10% and 6% respectively. Based on this model, the feedback-directed search finds a type-correct subset of type annotations that can produce complete and type-correct annotations for 42% to 64% of all files. Comparing TypeWriter with a traditional, static type inference shows that both techniques complement each other and that TypeWriter predicts many more types than traditional type inference. In summary, this paper makes the following contributions:

- A combination of probabilistic type prediction and search-based validation of predicted types. The feedback-directed search for type-correct types can be used with any probabilistic type predictor and any gradual type checker.
- A novel neural type prediction model that exploits both code context and natural language information.
- Empirical evidence that the approach is effective for type-annotating large-scale code bases with minimal human effort.

The initial experience from using TypeWriter at Facebook on a code base that powers tools used by billions of people has been positive.

2 APPROACH

Figure 2 gives a high-level overview of the TypeWriter approach. The input to TypeWriter is a corpus of code where some, but not all types are annotated. The approach consists of three main parts. First, a lightweight static analysis extracts several kinds of information from the given code (Section 2.1). The extracted information includes programming structure information, such as usages of a function’s arguments, and natural language information, such as identifier names and comments. Next, a neural type predictor learns from the already annotated types and their associated information how to predict missing types (Section 2.2). Once trained, this model can predict likely types for currently unannotated parts of the code. Finally, a feedback-directed search uses the trained model to find a type assignment that is consistent and type-correct according to a static, gradual type checker (Section 2.3). The overall output of TypeWriter is code with additional type annotations.

2.1 Static Extraction of Types and Context Information

The first part of TypeWriter is an AST-based static analysis that extracts types and context information useful to predict types. The analysis is designed to be lightweight and easy to apply to other programming languages. We currently focus on function-level types, i.e., argument types and return types. These types are particularly important for two reasons: (i) Given function-level types, gradual type checkers can type-check the function bodies by inferring the types of (some) local variables. (ii) Function-level types serve as interface documentation. For each type, the static analysis gathers four kinds of context information, which the following describes and illustrates with the example in Figure 3.

Identifier names associated with the to-be-typed program element. As shown by prior work [18, 22], natural language information embedded in source code can provide valuable hints about program properties. For example, the argument names name and do propagate in Figure 3 suggest that the arguments may be a string and a boolean, respectively. To enable TypeWriter to benefit from such hints, the static analysis extracts identifier names associated with each function signature. Specifically, the analysis extracts the name of each function and the name of each function argument.

Code occurrences of the to-be-typed program element. In addition to the above natural language information, TypeWriter exploits
Static analysis Neural type prediction Search for

If any of the above information is missing, the corresponding elements of the tuple are filled with a placeholder. In particular, the static analysis extracts the above also for unannotated types, to enable TypeWriter to predict types based on the context.

2.2 Neural Type Prediction Model

Given the extracted types and context information, the next part of TypeWriter is a neural model that predicts the former from the latter. We formulate the type prediction problem as a multi-class classification problem, where the model predicts a probability distribution over a fixed set of types. The neural type prediction...
model utilizes all four kinds of information described in Section 2.1. To this end, the model has four submodels, each of which processes one kind of information, and a component that combines all four kinds of information into a single type prediction. The middle part of Figure 2 summarizes the architecture of the neural network, which we explain in more detail in the following. The neural architecture is the same for predicting argument types and return types.

To represent identifier names, source code tokens, and words in comments in a way suitable for learning, TypeWriter requires a vector representation for each of them. For this purpose, the approach learns two embeddings, i.e., mappings of names, tokens, or words into a continuous vector representation. The first embedding, called the code embedding, $E_{\text{code}}$, maps an identifier name or a code token into a real-valued dense vector. To learn the code embedding, we build on Word2Vec [20], a state-of-the-art technique for learning embeddings from the context in which a word occurs. Specifically, we tokenize each file in the corpus and feed these sequences of tokens into Word2Vec. Tokens that correspond to identifier names are further preprocessed and tokenized using a helper function $\text{prep()}$ explained below. The second embedding, called the word embedding, $E_{\text{word}}$, maps a natural language word into a real-valued vector. Similar to the code embedding, we learn the word embedding based on Word2Vec. However, this time by feeding all comments extracted from the code corpus into Word2Vec.

### 2.2.1 Learning from Identifiers

This neural submodel learns from the identifier names of functions and function arguments. As a first step, TypeWriter preprocesses each identifier using the helper function $\text{prep()}$. This helper function tokenizes the given identifier based on the snake-case and camel-case conventions, transforms each word into a lowercase case, and lemmatizes each word. Lemmatization is a standard technique well-known in natural language processing, which maps inflected forms of a word to its dictionary form.

After this preprocessing, TypeWriter composes all identifier information associated with a type into a sequence. The vector starts with the words in the name of the to-be-typed program element, followed by a separator $s$ and the names of all other identifiers extracted for the function. Given argument type information $(n_{\text{fct}}, n_{\text{args}}, N_{\text{args}}, c, U, t)$, the sequence is

$$\text{prep}(n_{\text{arg}}) \circ s \circ \text{prep}(n_{\text{fct}}) \circ \text{prep}(N_{\text{args}})$$

where $\circ$ flattens and concatenates sequences. Similar, given return type information $(n_{\text{fct}}, N_{\text{args}}, c, R, t)$, the sequence is

$$\text{prep}(n_{\text{fct}}) \circ s \circ \text{prep}(N_{\text{args}})$$

TypeWriter learns from these sequences of words by summarizing them into a single vector using a recurrent neural network (RNN). Each word in a sequence is mapped to a vector using the code embedding $E_{\text{code}}$. Because RNNs expect fixed-length sequences, we pad sequences that are too short and truncate sequences that are too long (default length: 10). The RNN uses LSTM cells and is bi-directional, enabling the model to reason about both forward and backward relations between words. The final hidden states of the RNN serve as a condensed vector representation, $v_{\text{ids}}$, of all identifier-related hints.

### 2.2.2 Learning from Token Sequences

This neural submodel learns from source code information associated with a type. The overall approach is similar to the way TypeWriter learns from identifiers: compose all relevant tokens into a single sequence, represent each token as an embedding vector, and summarize the sequence into a single vector using an RNN. For arguments, the approach considers the usages $U$ of the argument in the function body. Given a usage $U_1, \ldots, U_k$ in $U$, TypeWriter represents it as a sequence of vectors by mapping each token to its code embedding, i.e., $E_{\text{code}}(U_1), \ldots, E_{\text{code}}(U_k)$. Likewise, for return types, the approach constructs a sequence of code embeddings by mapping each token in the return statements $R$ to its embedding. Before feeding these sequences into an RNN, we bound the length of each token sequence (default: $k = 7$) and discard any words beyond this bound. Next, we feed the sequence of embeddings into another RNN, which summarizes the comment information into a single, fixed-length vector $v_{\text{comments}}$.

### 2.2.3 Learning from Comments

This neural submodel learns type hints from comments associated with a function. To this end, TypeWriter splits a given comment into a sequence of words and maps each word to its word embedding using $E_{\text{word}}$. We bound the length of the sequence to a fixed value (default: 20), and discard any words beyond this bound. Next, we feed the sequence of embeddings into another RNN, which summarizes the comment information into a single, fixed-length vector $v_{\text{comments}}$.

### 2.2.4 Learning from Available Types

The final kind of information that TypeWriter learns from is the set of types available in the current source code file. The approach assumes a fixed-size vocabulary $T$ of types (default size: 1,000). This vocabulary covers the vast majority of all type occurrences because most type annotations either use one of the built-in primitive types, e.g., $\text{str}$ or $\text{bool}$, common non-primitive types, e.g., $\text{List}$ or $\text{Dict}$, or their combinations, e.g., $\text{List}[$int$]$ or $\text{Dict}[$str$, \text{bool}]$. Any types beyond the type vocabulary are represented as a special “unknown” type.

To represent which types are available, we use a vector of size $T$, called the type mask. Each element in this vector represents one type, and an element is set to one if the type is present and to zero otherwise. Because the dimension of the vector $v_{\text{availTypes}}$ of available types is relatively small, there is no need to further reduce the vector, and it is passed as-is into the part of the neural model that predicts the most likely type.

### 2.2.5 Predicting the Most Likely Type

The four submodels presented above each process one kind of hint about the type of a program element. The final step of the neural type prediction model is to combine these four kinds of information and to predict the most likely types. To this end, the model concatenates the four vectors $v_{\text{ids}}, v_{\text{code}}, v_{\text{comments}}$, and $v_{\text{availTypes}}$, into a single vector. The concatenated vector is then passed through a fully connected layer, which yields the final output of the neural model. The output layer has size $|T|$ and again, each element represents one of the types in the type vocabulary. By applying the softmax function to the output layer, the prediction can be interpreted as a probability distribution over the set of available types. For example, suppose the type vocabulary had only four types $\text{int}$, $\text{bool}$, $\text{None}$, and $\text{List}$, and that the output vector is $[0.1, 0.6, 0.2, 0.1]$. In this case, the model would predict that $\text{bool}$ is the by far most likely type, following by $\text{None}$. Michael Pradel, Georgios Gousios, Jason Liu, and Satish Chandra
There are two ways to handle uncertainty and limited knowledge in the model. First, we interpret the predicted probability of a type as a confidence measure and only suggest types to a user that are predicted with a confidence above some configurable threshold. Second, we encode types not included in the fixed-size type vocabulary as a special “unknown” type. The model hence learns to predict “unknown” whenever none of the types in the vocabulary fit the given context information. During prediction, TypeWriter never suggests the “unknown” type to the user, but instead does not make any suggestion in case the model predicts “unknown”.

To train the neural type prediction model, TypeWriter relies on already type-annotated code. Given such code, the approach creates one pair of context information and type for each argument type and for each return type. These pairs then serve as training data to train the parameters of the different neural submodels. We use standard stochastic gradient descent, using the Adam optimizer, and cross-entropy as the loss function. The entire neural model is learned jointly, enabling the model to summarize each kind of type hint into the most suitable form for the final type prediction task and to decide which type hints to consider for a given query.

We train two separate models for argument types and function types, each learned from training data consisting of only one kind of type. The rationale is that some of the available type hints need to be interpreted differently depending on whether the goal is to predict an argument type or a return type. To predict currently missing types, TypeWriter extracts all available type hints and feeds them into the model trained for this kind of type.

2.3 Feedback-guided Search for Consistent Types

The neural type prediction model provides a list of $k$ predictions, ordered by likelihood, for each missing type annotation. Given a set of locations for which a type annotation is missing (type slots) and a list of probabilistic predictions for each slot, the question is which of the suggested types to actually assign to the slots. A naïve approach might fill each slot with the top-ranked type. This may work in some cases; however, because the neural model may mis-predict some types, this approach may yield type assignments where the added annotations are not consistent with each other or the remaining program. To avoid introducing type errors, TypeWriter leverages an existing gradual type checker as a filter to validate candidate type assignments. Such type checkers exist for all popular dynamically typed languages that support optional type annotations, e.g., pyre and mypy for Python, and flow for JavaScript. TypeWriter exploits feedback from the type checker to guide a search for consistent types, as indicated in the sections below.

2.3.1 Search Space. Given a set $S$ of type slots and $k$ predicted types for each slot, we formulate the problem of finding a consistent type assignment as a combinatorial search problem. The search space consists of the set of possible type assignments $P(S)$. For $|S|$ type slots and $k$ possible types for each slot, there are $(k + 1)^{|S|}$ type assignments (the +1 is for not assigning any of the predicted types).

2.3.2 Feedback Function. The search procedure aims to find a type assignment that minimizes the number of unfilled type slots and precludes type errors from being introduced by the assignment. Exhaustrively exploring the entire search space is practically infeasible for files with many missing types, because invoking the gradual type checker is relatively expensive (typically, in the order of several seconds per file). Instead, TypeWriter uses a feedback function to efficiently steer toward the most promising type assignments.

The feedback function is based on two values, both of which the search wants to minimize:

- $n_{\text{missing}}$: The number of missing types.
- $n_{\text{errors}}$: The number of type errors.

TypeWriter combines these into a weighted sum $\text{score} = v \cdot n_{\text{missing}} + w \cdot n_{\text{errors}}$. By default, we set $v = 1$ and $w = 2$, which is motivated by the fact that adding an incorrect type often leads to an additional error. By giving type errors a higher weight, we discourage the search from introducing type errors.

A particular challenge in measuring $n_{\text{errors}}$ is that adding a type annotation to a function may cause type errors, irrespective of what type gets added. Since many gradual type checkers only type-check a function body if the function has at least its return type annotated, it may be the case that adding any type, including the correct type, as the return type may yield additional type errors. As these type errors do not provide feedback about whether a newly added type is correct, we ignore them in $n_{\text{errors}}$. Before beginning to search, TypeWriter mines these errors by initially adding a correctly returned type to functions featuring return type slots and checking which type errors appear in the function bodies.

2.3.3 Exploring the Search Space. To explore the space of assignments, TypeWriter gradually builds a search tree. Each node in the tree encodes the current state of exploration, while branches denote a potential action to perform in order to continue the exploration. There are three types of actions: adding a type, removing a type, and replacing a type with another type.

The search that TypeWriter implements is optimistic: It assumes that most predictions are correct and then replaces or removes incorrect types to validate the type assignment. The search starts by adding all top-1 predictions at once, and then removes or replaces individual types to fix type errors. To select the next type to remove or replace, the search computes the difference in line numbers between each type error and each added type, and then removes/swaps the type with the minimal distance. Intuitively, this type is more likely to be the cause of a type error than a randomly selected type. The reason for relying on line numbers as the interface between the type checker and TypeWriter is to enable plugging any type checker into our approach. The exploration continues until either all potential states have been explored or pruned, or until the feedback score becomes zero. If the search returns a type assignment that still contains type errors, then it is discarded. 1

TypeWriter implements two variants of the search, a greedy and a non-greedy one. The greedy strategy aggressively explores children of states that decrease the feedback score and prunes children of states that increase it. The non-greedy strategy prioritizes actions that minimize the unfilled type slots, but performs no pruning. Effectively, the non-greedy search can explore a larger part of the solution space at the expense of time.

1This can occur if the search limit is too low, but is also an artifact of the scoring function, which could be tuned based on finer search requirements.
We structure our evaluation along four research questions. TypeWriter is developed and evaluated within Facebook. As the implementation of TypeWriter builds upon a variety of tools in the Python ecosystem. For obtaining embeddings for words and tokens, we pre-train a Word2Vec model using the gensim library. The search phase of TypeWriter builds upon the RedBaron library to add types to existing Python files. We use pyre for static type checking.

3 IMPLEMENTATION

The implementation of TypeWriter builds upon a variety of tools in the Python ecosystem. For the static analysis phase, we apply a data extraction pipeline consisting of Python's own ast library to parse the code into an AST format, and NLTK and its WordNetLemmatizer module to perform standard NLP tasks (lemmatization, stop word removal). The pipeline is parallelized so that it handles multiple files concurrently. The neural network model is implemented in PyTorch. For obtaining embeddings for words and tokens, we pre-train a Word2Vec model using the gensim library. The search phase of TypeWriter builds upon the RedBaron library to add types to existing Python files. We use pyre for static type checking.

4 EVALUATION

We structure our evaluation along four research questions.

RQ 1: How effective is TypeWriter’s model at predicting argument and return types, and how does it compare to existing work?

RQ 2: How much do the different kinds of context information contribute to the model’s prediction abilities?

RQ 3: How effective is TypeWriter’s search?

RQ 4: How does TypeWriter compare to traditional static type inference?

4.1 Datasets

TypeWriter is developed and evaluated within Facebook. As the internal code base is not publicly available and to ensure that the presented results are replicable, we use two datasets:

**Internal code base** We collect Python from a large internal code repository.

**OSS corpus** We search GitHub for all projects tagged as python3. We also search Libraries.io for all Python projects that include mypy as a dependency. We then remove all projects that have less than 100 stars on GitHub, to ensure that the included projects are of substantial public interest.

The resulting dataset statistics can be found in Table 1. The internal dataset was much larger in size, even though we cannot disclose its exact size. Both datasets are comparable in terms of the percentage of annotated code. By restricting the type vocabulary to a fixed size, we exclude around 10% of all type occurrences for both datasets. This percentage is similar for both datasets, despite their different sizes, because types follow a long-tail distribution, i.e., relatively few types account for the majority of all type occurrences. We ignore some types because they are trivial to predict, such as the return type of __str__ or the type of self arguments.

4.2 Examples

Figure 4 shows examples of successful and unsuccessful type predictions (GitHub: augustin/websockets).

Table 1: Internal and open-source datasets.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Internal</th>
<th>OSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Repositories</td>
<td>1</td>
<td>498</td>
</tr>
<tr>
<td>Files</td>
<td>*</td>
<td>39.002</td>
</tr>
<tr>
<td>Lines of code</td>
<td>*</td>
<td>5.8M</td>
</tr>
<tr>
<td>Functions</td>
<td>*</td>
<td>289,936</td>
</tr>
<tr>
<td>... with return type annotation</td>
<td>8.9%</td>
<td>33,952 (11.7%)</td>
</tr>
<tr>
<td>... with comment</td>
<td>20.6%</td>
<td>83,395 (28.8%)</td>
</tr>
<tr>
<td>... with both</td>
<td>2.3%</td>
<td>12,154 (4.2%)</td>
</tr>
<tr>
<td>... ignored because trivial</td>
<td>7.9%</td>
<td>24,201 (8.3%)</td>
</tr>
<tr>
<td>Arguments</td>
<td>*</td>
<td>499,531</td>
</tr>
<tr>
<td>... with type annotation</td>
<td>6.5%</td>
<td>48,710 (9.8%)</td>
</tr>
<tr>
<td>... ignored because trivial</td>
<td>34.5%</td>
<td>194,488 (38.9%)</td>
</tr>
<tr>
<td>Types</td>
<td>*</td>
<td>5,475</td>
</tr>
<tr>
<td>... occurrences ignored (out of vocab.)</td>
<td>10.1%</td>
<td>9.8%</td>
</tr>
<tr>
<td>Training time (min:sec)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>... parsing</td>
<td>several minutes</td>
<td>1:45</td>
</tr>
<tr>
<td>... training embeddings</td>
<td>several minutes</td>
<td>2:29</td>
</tr>
<tr>
<td>... training neural model</td>
<td>several minutes</td>
<td>2:20</td>
</tr>
</tbody>
</table>

* = not available for disclosure

Example 1

```python
# Commit: e1417d4
# github.com/aaugustin/websockets/blob/master/src/websockets/headers.py
def add(token : str, ...):
    # Incorrect annotation of return type: expected Tuple[str, int]
    return
```

Example 2

```python
# Commit: 46ddc64
# github.com/PrefectHQ/prefect/blob/master/src/prefect/cli/auth.py
def parse_token(header, pos) -> Tuple[str, str]:
    match = _token_re.match(header, pos)
    ... return match.group(), match.end()
```

![Figure 4: Examples of successful and unsuccessful type predictions (GitHub: augustin/websockets).](image-url)
prec = work on predicting types, including JSNice [23] and DeepTyper [13],

Precise to work on predicting types, including JSNice [23] and DeepTyper [13],

The recall are good but less high than precision, indicating that

TypeWriter: Neural Type Prediction with Search-based Validation
Conference’17, July 2017, Washington, DC, USA

TypeWriter and NL2Type are higher in the case of the

4.4 RQ 2: Comparison with Simpler Variants of

TypeWriter prediction model more in the

Overall, the combined information of natural language, token

Results. Table 2 presents the results for RQ 1. Our neural model

Table 2: Effectiveness of neural type prediction.

<table>
<thead>
<tr>
<th>Corpus</th>
<th>Task</th>
<th>Model</th>
<th>Prec.</th>
<th>Recall</th>
<th>F1-score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Top-1</td>
<td>Top-3</td>
<td>Top-5</td>
<td>Top-1</td>
</tr>
<tr>
<td>Internal</td>
<td>ReturnPrediction</td>
<td>TypeWriter</td>
<td>0.72</td>
<td>0.87</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>NL2Type</td>
<td>0.59</td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Naive baseline</td>
<td>0.14</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ArgumentPrediction</td>
<td>TypeWriter</td>
<td>0.61</td>
<td>0.85</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>NL2Type</td>
<td>0.52</td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Naive baseline</td>
<td>0.09</td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CombinedPrediction</td>
<td>TypeWriter</td>
<td>0.64</td>
<td>0.85</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>NL2Type</td>
<td>0.54</td>
<td>0.80</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Naive baseline</td>
<td>0.11</td>
<td>0.18</td>
<td></td>
</tr>
<tr>
<td>OSS</td>
<td>ReturnPrediction</td>
<td>TypeWriter</td>
<td>0.67</td>
<td>0.76</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>NL2Type</td>
<td>0.59</td>
<td>0.69</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Naive baseline</td>
<td>0.19</td>
<td>0.27</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ArgumentPrediction</td>
<td>TypeWriter</td>
<td>0.61</td>
<td>0.77</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>NL2Type</td>
<td>0.55</td>
<td>0.72</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Naive baseline</td>
<td>0.06</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CombinedPrediction</td>
<td>TypeWriter</td>
<td>0.65</td>
<td>0.80</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>NL2Type</td>
<td>0.59</td>
<td>0.73</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Naive baseline</td>
<td>0.12</td>
<td>0.19</td>
<td></td>
</tr>
</tbody>
</table>

Metrics. We evaluate the effectiveness of TypeWriter’s neural type predictor by splitting the already annotated types in a given dataset into training (80%) and validation (20%) data. The split is by file, to avoid mixing types within a single file. Once trained on the training data, we compare the model’s predictions against the validation data, using the already annotated types as the ground truth. We compute precision, recall, and F1-score, weighted by the number of type occurrences in the dataset. Similarly to previous work [18], if the prediction model cannot predict a type for a type slot (i.e., returns “unknown”), we remove this type slot from the calculation of precision. Specifically, we calculate precision as \( prec = \frac{n_{corr}}{n_{all}} \), where \( n_{corr} \) is the number of correct predictions and \( n_{all} \) is the number of type slots for which the model does not return “unknown”. We calculate recall as \( recall = \frac{n_{corr}}{|D|} \), where \( |D| \) is total number of type slots in the examined dataset. We report the top-k scores, for \( k \in \{1, 3, 5\} \).

Baseline models. We compare TypeWriter’s top-k predictions against two baseline models. The naïve baseline model considers the ten most frequent types in the dataset and samples its prediction from the distribution of these ten types, independently of the given context. For example, it predicts none as a return type more often than List[str] because None is used more as a return type than List[str]. The NL2Type baseline is a re-implementation of the NL2Type model [18] for Python, which also learns from natural language information associated with a type, but does not consider code context or available types. We pick NL2Type as the state-of-the-art baseline because it has been shown to outperform prior work on predicting types, including JSNice [23] and DeepTyper [13], albeit for a different language.

Results. Table 2 presents the results for RQ 1. Our neural model achieves moderate to high precision scores, e.g., 64% in the top-1 and 91% in the top-5 for CombinedPrediction on the internal dataset. The recall are good but less high than precision, indicating that the prediction model is fairly confident when it makes a prediction, but abstains from doing so when it is not. All models have slightly worse performance on the OSS dataset; we attribute this difference to the size of the training set. It is interesting to note that the top-3 scores are significantly higher than top-1 in all cases; this fact suggests that combinatorial search among top-3 scores will be able to uncover more correct type combinations.

Compared to the baselines, TypeWriter outperforms both the state-of-the-art and the naïve baseline across all metrics for both datasets and all three prediction tasks. The differences between TypeWriter and NL2Type are higher in the case of the ReturnPrediction task. The context information, as obtained by analyzing token sequences, is apparently helping the TypeWriter prediction model more in the ReturnPrediction task; this is probably because name-based analysis is not enough to distinguish variable uses within function bodies.

4.4 RQ 2: Comparison with Simpler Variants of the Neural Model

The main novelty of TypeWriter’s prediction component is the inclusion of code context information and a local type mask in the prediction model. To explore the influence of the different type hints considered by TypeWriter, we perform an ablation study. Specifically, we turn off parts of the model, both in training and in testing, and then measure top-1 precision and recall at various prediction threshold levels. We start with the full model (typewriter) and then we remove, in order, the type mask, the token sequences, and without a type mask. The results of the ablation study can be seen in Figure 5.

Overall, the combined information of natural language, token sequences, and type masks helps TypeWriter to perform better than
previous models, such as NL2Type. The main contributor to this improvement is the token sequences component; across datasets and tasks, its removal brings the performance of TypeWriter down to NL2Type levels. Moreover, the results seem to reinforce the main thesis of the Malik et al. [18] work regarding the relation between natural language and types used. If we remove the argument and function naming information from TypeWriter, its performance drops significantly below NL2Type levels.

Contrary to our initial expectations, the type mask component is not contributing significantly in the ReturnPrediction task, while only slightly improving the ArgumentPrediction results. We attribute this to the current implementation of the type mask data extraction process: the extractor currently neither performs an in-depth dependency resolution to retrieve the full set of types available in the processed file’s name space, nor does it track type renames (e.g., `import pandas as pd`). The low predictive capability of comments can be explained by the fact that only a small number of the methods in both our datasets actually have documentation. We use the same prediction model trained on the Facebook dataset as in Section 4.3.

Table 3 shows the results on two levels: individual type annotations and files. On the annotation-level, column `type-correct` shows how many types the solution returned by the search annotates correctly. Column `ground truth match` shows how many of all added annotations match the original, developer-produced type annotations. On the file-level, a complete and type-correct solution is a file that TypeWriter fully annotates without type errors. This metric does not include files where TypeWriter discovers a type-correct, but partially annotated solution. The ground truth match is the subset of the complete and type-correct solutions, where the solution is identical to the ground truth for all types in the file. It is possible to find a type-correct annotation that does not match the ground truth. As an illustrative example, TypeWriter may correctly annotate the return type of a function as a `str`, but a human expert might choose a more precise type `List[str]`. Both are type-correct, but the human annotation provides more guarantees.

Both search strategies successfully annotate a significant fraction of all types. On the annotation-level, they add between 54% and 75% of all types in a type-correct way, out of which 46% to 65% match the ground truth, depending on the search strategy. On the file-level, TypeWriter completely annotates 42% to 64% of all files, and 34% to

### Table 3: Effectiveness of various search strategies for type inference.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Top-k</th>
<th>Annotations</th>
<th>Files</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Type-correct</td>
<td>Ground truth match</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Complete-type correct</td>
<td>Ground truth match</td>
</tr>
<tr>
<td>Greedy search</td>
<td>1</td>
<td>215 (70%)</td>
<td>194 (63%)</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>230 (75%)</td>
<td>196 (64%)</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>231 (75%)</td>
<td>198 (65%)</td>
</tr>
<tr>
<td>Non-greedy search</td>
<td>1</td>
<td>216 (71%)</td>
<td>195 (64%)</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>178 (58%)</td>
<td>148 (48%)</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>164 (54%)</td>
<td>141 (46%)</td>
</tr>
<tr>
<td>Upper bound</td>
<td>1</td>
<td>–</td>
<td>215 (70%)</td>
</tr>
<tr>
<td>(prediction)</td>
<td>3</td>
<td>–</td>
<td>250 (82%)</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>–</td>
<td>255 (83%)</td>
</tr>
<tr>
<td>Pyre Infer</td>
<td>–</td>
<td>106 (35%)</td>
<td>78 (25%)</td>
</tr>
</tbody>
</table>
TypeWriter: Neural Type Prediction with Search-based Validation

Table 4: Comparison of TypeWriter and a traditional, static type inference (pyre infer).

<table>
<thead>
<tr>
<th></th>
<th>Top-3 (greedy)</th>
<th>Top-3 (non-greedy)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total type slots</td>
<td>306</td>
<td>306</td>
</tr>
<tr>
<td>... added by TypeWriter only</td>
<td>145</td>
<td>110</td>
</tr>
<tr>
<td>... added by pyre infer only</td>
<td>9</td>
<td>11</td>
</tr>
<tr>
<td>... added by both tools</td>
<td>85</td>
<td>68</td>
</tr>
<tr>
<td>... same prediction</td>
<td>65</td>
<td>51</td>
</tr>
<tr>
<td>... neither could predict</td>
<td>67</td>
<td>117</td>
</tr>
</tbody>
</table>

40% of all files perfectly match the developer annotations. Comparing the two search strategies, we find that, at the annotation-level, greedy search discovers more type-correct annotations with top-3 and top-5 predictions, while non-greedy search actually finds fewer annotations. This is due to the exponential increase in search space, which, for a non-greedy search, provides fewer guarantees that it will find a type-correct solution. This suggests that the greedy search is able to explore a more promising part of the search space. At the file-level, both search approaches provide more annotations and fully annotate more files as the number of available predictions per slot increases. In both the greedy and the non-greedy case, a search using the top-5 results does not improve the outcome significantly; this mirrors the neural model’s moderate improvement of recall when \(k\) increases beyond 3. The choice between greedy and non-greedy search also affect efficiency: On average, the non-greedy search takes three times longer to complete than the greedy-search.

To better understand how effective the search is, we also show how many ground truth-matching types the top-\(k\) predictions include ("upper bound (prediction)"). Note that these numbers are a theoretical upper bound for the search, which cannot be achieved in practice because it would require exhaustively exploring all combinations of types predicted within the top-\(k\). Comparing the upper bound with the results of the search shows that the search gets relatively close to the maximum effectiveness it could achieve. For example, a top-3 exploration with greedy search finds a complete and type-correct solution that matches the ground truth for 19 files, while the theoretical upper bound are 21 files. We leave developing further search strategies, e.g., based on additional heuristics, for future work.

Overall, the results show that a greedy search among top-\(k\) types can uncover a more types when given more predictions, while also maintaining type correctness. \(k = 3\) provides the best balance between annotation performance and run time. While a non-greedy search should not immediately be disregarded, it should be considered in terms of how exhaustive the developer will allow the search to be.

4.6 RQ 4: Comparison with Static Type Inference

We compare TypeWriter with a state-of-the-art, static type inference tool pyre infer. The type inference is part of the pyre type checker and is representative of conservative static analysis-based type inference that adds only types guaranteed to be type-correct. We run pyre infer on the same set of randomly chosen, fully annotated files as in Section 4.5 and then compare the added annotations with TypeWriter top-3 search results. Tables 3 (bottom) and 4 show the results.

In a head to head comparison, TypeWriter is able to provide type-correct predictions 3 times the files that pyre infer can. It also discovers significantly more types, adding a total of 230 types, whereas pyre infer adds only 94. Additionally, of the 85 type slots for which both tools suggest a type, the suggestions are the same in 65 cases. Effectively, the types that TypeWriter suggests are a superset of those inferred by pyre infer, as pyre infer does not uniquely find many types. To further illustrate the differences, we plot the distribution of the top-10 correctly predicted types in Figure 6. We see that pyre infer can infer more precise types, but the majority of its inferences are on methods with no return types. Moreover, some of the inferred types are of dubious usefulness (e.g., `Optional[Optional[Context]]`) indicating the difficulty of applying static type inference on dynamically-typed languages and reinforcing our thesis on the value of prediction-based type inference.

5 DISCUSSION

Effectiveness of neural type prediction. TypeWriter implements the first neural type prediction model for Python. As all existing type prediction models [13, 18, 23] target JavaScript code, it is difficult to draw conclusions as to whether the TypeWriter architecture is the best for the task. Two facts seem to suggest so: i) TypeWriter is better by a comfortable margin than a re-implementation of the best in class JavaScript model (NL2Type), and ii) TypeWriter’s performance is stable across two very different datasets.

Type-correctness vs. soundness. Due to the way current Python type checkers work, the types that TypeWriter produces are guaranteed to be type-correct within the context of a given module (typically, a directory). Type correctness is different from type soundness, as the later can only be verified using human intuition. This means that if a module is used within another context, the type checker might invalidate an initially correct prediction. In turn, this makes TypeWriter a soundy [17], rather than a sound approach.
Limited type vocabulary. TypeWriter is only able to predict types that are part of its type vocabulary. When the size of the type vocabulary is configured at 1000 types, it can account for 90% of the available types in both our datasets. However, as software evolves, developers create new types or change the names of existing ones. This may lead to situations where the model would predict a wrong type because its name changed or because it simply does not know that the type exists. The out-of-vocabulary problem is well known in software engineering research; in fact, Hellendoorn and Devanbu [14] argue that it is the key challenge in applying deep models on code. Very recent work for by Karampatsis and Sutton [16] uses sub-word information to account for neologisms with very good results. We believe that TypeWriter would benefit significantly from such an approach for embedding identifier names, as it would enable it to learn semantically similar name variants (e.g., AbstractClass and Class or List and List[str]).

Further improvements. TypeWriter is a prototype stemming from a general effort within Facebook to make their Python code base more robust. On an alpha testing basis, it has already been used to generate type annotations for individual files that have been accepted by developers. The following is a list of improvements that we are exploring before putting it into production use:

- Better data: The ablation study results suggest that type masks and documentation components of the TypeWriter model are only marginally contributing to its prediction capabilities. This goes against both intuition and published work: in [18], the authors show that code documentation is an important signal. Unfortunately, for both our datasets, the documentation coverage is not high; we could however exploit the fact that highly used libraries, such as Flask or the Python standard library itself feature both type annotations (in the typeshed repository) and excellent documentation. Moreover, we can obtain better type masks using lightweight dependency analysis, such as importlab,5 to identify all types that are in context. Furthermore, teaching the model to learn how types are defined could allow it to automatically pick up all types associated with the existing context.

- Faster search feedback: The execution speed of TypeWriter is currently constrained by the type checker used to obtain feedback. One natural way to improve this would be to integrate the TypeWriter type predictor into a static type inference loop: when the type inference cannot predict a type for a location, it can ask the type checker (mypy) as part of Python 3.5 version in 2015. The combination of the two enables gradual typing of existing code bases, where the type checker will only check the annotated parts of the code. Similar approaches to gradual typing have also been explored by the research community [28]. Since 2015, type annotations have seen adoption in several large-scale Python code bases, with products such as Dropbox and Instagram,5 reportedly having annotated large parts of their multi-million line code bases. TypeWriter helps reduce the manual effort required for such a step.

- Reinforced learning: As with most neural models, TypeWriter can benefit from more data. One idea worth exploring is to apply TypeWriter in batches, consisting of application of an initial set of neural predictions, reviewing proposed types through the normal code review process at Facebook and then retrain the model on the new data. At the scale of the Facebook code base, we expect that the feedback obtained (accepted, modified and rejected suggestions) could be used to improve the learning process.

6 RELATED WORK

Type inference for dynamic languages. Static type inference [4, 7, 12, 15] computes types using, e.g., abstract interpretation or type constraint propagation. These approaches are sound by design, but due to the dynamic nature of some languages, they often infer only simple or very generic types [7, 15]. They also require a significant amount of context, usually a full program and its dependencies. Dynamic type inference [3, 24] tracks data flows between functions, e.g., while executing a program’s test suite. These approaches capture precise types, but they are constrained coverage. TypeWriter differs from those approaches in two key aspects: i) it only requires limited context information, i.e., a single a source code file, ii) it does not require the program to be executed and hence can predict types in the absence of a test suite or other input data.

Probabilistic type inference. The difficulty of accurately inferring types for dynamic programming languages has led to research on probabilistic type inference. JSNice [23] models source code as a dependency network of known (e.g., constants, API methods) and unknown facts (e.g., types); it then mines information from large code bases to quantify the probability of two items being linked together. Xu et al. [30] predict variable types based on a probabilistic combination of multiple uncertain type hints, e.g., data flows and attribute accesses. They also consider natural language information, but based on lexical similarities of names, and focus on variable types, whereas TypeWriter focuses on function types. DeepTyper [13] uses a sequence-to-sequence neural model to predict types based on a bi-lingual corpus of TypeScript and JavaScript code. Like TypeWriter, NL2Type [18] uses natural language information. Our evaluation directly compares with a Python re-implementation of NL2Type, as NL2Type has been shown to outperform prior work. Besides advances in the probabilistic type prediction model itself, the more important contribution of our work is to address the imprecision and combinatorial explosion problems of probabilistic type inference. In principle, any of the above techniques can be combined with TypeWriter’s search-based validations to obtain type-correct types in reasonable time.

Type checking and inference for Python. The Python community (PEP-484 [26]) introduced a type annotation syntax along with a type checker (mypy) as part of Python 3.5 version in 2015. The combination of the two enables gradual typing of existing code bases, where the type checker will only check the annotated parts of the code. Similar approaches to gradual typing have also been explored by the research community [28]. Since 2015, type annotations have seen adoption in several large-scale Python code bases, with products such as Dropbox and Instagram,5 reportedly having annotated large parts of their multi-million line code bases. TypeWriter helps reduce the manual effort required for such a step.

Machine learning on code. Our neural type prediction model is motivated by a stream of work on machine learning-based program analyses [2]. Beyond type prediction, others have proposed learning-based techniques to find programming errors [22], predict variable and method names [1, 23, 27], search code [9, 25], detect clones [29, 31], predict code edits [32], and automatically fix

5Dropbox Blog: How we rolled out one of the largest Python 3 migrations ever

5Instagram Engineering Blog: Introducing open source MonkeyType
TypeWriter: Neural Type Prediction with Search-based Validation

bugs [5, 10]. TypeWriter contributes a novel model for predicting types and a search-based combination of predictive models with traditional type checking.

Search-based software engineering. Our search-based validation of types fits the search-based software engineering theme [11], which proposes to balance competing constraints in developer tools through metaheuristic search techniques. In our case, the search balances the need to validate an exponential number of combinations of type suggestions with the need to efficiently annotate types.

7 CONCLUSIONS

We present TypeWriter, a learning-based approach to the problem of inferring types for code written in Python. TypeWriter exploits the availability of partially annotated source code to learn a type prediction model and the availability of type checkers to refine and validate the predicted types. TypeWriter’s learned model can readily predict correct type annotations for half of the type slots on first try, whereas its search component can help prevent annotating code with wrong types. Combined, the neural prediction and the search-based refinement helps annotate large code bases with minimal human intervention, making TypeWriter the first practically applicable learning-based tool for type annotation.

We are currently in the process of making TypeWriter available to developers at Facebook. The initial experience from applying the approach on a code base that powers tools used by billions of people has been positive: several hundreds suggested types have already been accepted with minimal changes.

REFERENCES


