Test-Case Generation for Finding Neural Network Bugs

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ABSTRACT
As neural networks are increasingly included as core components of safety-critical systems, developing effective testing techniques specialized for them becomes crucial. The bulk of the research has focused on testing neural-network models (for instance, their robustness and reliability as classifiers). But neural-network models are defined by writing programs (usually written in a programming language like Python), and there is growing evidence that these neural-network programs often have bugs. Thus, being able to effectively test neural-network programs is instrumental to their dependability.

This paper presents ANNoTest: an approach to generating test inputs for neural-network programs. A fundamental challenge is that the dynamically-typed languages (e.g., Python) used to program neural networks cannot express detailed constraints about valid function inputs (e.g., vectors and matrices with certain dimensions). Without knowing these constraints, automated test-case generation is prone to producing many invalid inputs, which trigger spurious failures and are useless for identifying real bugs. To address this problem, we introduce a simple annotation language tailored for expressing valid function inputs in neural-network programs. ANNoTest inputs an annotated program, and uses property-based testing to generate random inputs that satisfy the validity constraints. In the paper, we also outline guidelines that help reduce the effort needed to write ANNoTest annotations.

We evaluated ANNoTest on 19 neural-network programs from Islam et al.’s survey [13], which we manually annotated following our guidelines—producing 6 annotations per tested function on average. ANNoTest automatically generated test inputs that revealed 94 bugs, including 63 bugs that the survey reported for these projects. These results suggest that ANNoTest can be a cost-effective approach to finding widespread bugs in neural-network programs.

1 INTRODUCTION
Neural networks have taken the (programming) world by storm. With their capabilities of solving tasks that remain challenging for traditional software, they have become central components of software systems implementing complex functionality such as image processing, speech recognition, and natural language processing, where they can reach performance at or near human level. These tasks are widely applicable to domains such as automotive and healthcare, where safety, reliability, and correctness are critical. Therefore, the software engineering (research) community has been hard at work designing techniques to assess and ensure the dependability of software with neural network (NN) components.

Testing techniques, in particular, are being extensively developed to cater to the specific requirements of NN (and, more generally, machine learning) systems [19]. Most of this research focuses on testing NN models: instances of a specific NN architecture, which are trained on some data and then used to classify or transform new data. Testing a NN model entails assessing qualities such as its robustness and performance as a classifier. However, neural networks are programs too: a NN model is usually implemented in a programming language like Python, using frameworks such as Keras or TensorFlow. There is clear evidence that these neural network programs tend to be buggy [12, 13]; therefore, an effective technique for finding these bugs would be practically very useful and complement the extensive work on NN model testing. This paper presents a novel contribution in this direction.

NN programs may seem simple by traditional metrics of complexity: for example, the average project size of the NN projects surveyed by Islam et al. [13] is just 2165 lines of code; and the majority of the bugs they found are relatively simple ones such as crashes and API misuses. Nevertheless, other characteristics make traditional test-case generation techniques ineffective to test such programs. As we mentioned earlier, NN programs are written in dynamically typed languages like Python, where the type of variables is unknown statically. Therefore, generating valid inputs is challenging with techniques such as random testing and genetic algorithms, which typically assume a variable’s type is known [16]. Even if type annotations were available, NN programs routinely manipulate complex data structures—such as vectors, tensors, and other objects—whose precise "shape" is not expressible with the standard types (integers, strings, and so on). As we demonstrate with an example in Sec. 2, without such precise information automated test case generation tends to generate many invalid inputs that trigger spurious failures.

This paper presents ANNoTest: an approach to automatically generating bug-finding inputs for NN program testing. A key component of ANNoTest (described in detail in Sec. 3) is AN: a simple annotation language designed to concisely and precisely express the valid inputs of functions in NN programs. The AN annotation language supports expressing the kinds of constraints that are needed in NN programs (for example: a variable should be a vector of size from 2 to 5 with components that are positive integers). AN is also easily extensible to accommodate other constraints that a specific NN program may need to encode.

Given an annotated NN program, ANNoTest automatically generates unit tests for the program that span the range of valid inputs. The current implementation of ANNoTest uses property-based testing (more precisely, the Hypothesis\textsuperscript{1} [17] test-case generator) to generate test inputs that comply with the annotations. Using the AN language decouples specifying the constraints from the back-end used to generate the actual tests; therefore, different back-end tools could also be used that better suit the kinds of constraints used in a project’s annotations.
1 dense_layers = (depth - 4) / 3 # Bug: division / returns a float
2 # ... 23 more lines of code ...
3 HOW ANNOTEST WORKS

Fig. 1 overlooks the overall process followed by the ANNoTest approach. To test a NN program with ANNoTest, we first have to annotate its functions (including member functions, that is methods) using the AN annotation language (Sec. 3.1). This is the only step that is manual, since the annotations have to encode valid inputs of the tested functions. However, Sec. 3.2 provides guidelines that help structure the manual annotation process so that it only requires a reasonable amount of effort; furthermore, users do not need to annotate a whole program but only those functions that should be tested. Then, the ANNoTest tool inputs an annotated program and generates unit tests for it. To do this, it encodes the constraints expressed by the AN annotations in the form of test templates for the property-based test-case generator Hypothesis (Sec. 3.3); then, it runs Hypothesis which takes care of generating suitable tests. Finally, the generated unit tests can be run as usual to find which are passing and which are failing—and thus expose some bugs in the NN program (Sec. 3.4).

3.1 The AN Annotation Language

By writing annotations in the AN annotation language, developers can precisely express the valid inputs of a function in a NN program. To this end, AN provides type annotations (Sec. 3.1.1) and preconditions (Sec. 3.1.3), as well as an extension mechanism to define arbitrarily complex constraints (Sec. 3.1.2). In addition, AN offers a few auxiliary annotations (Sec. 3.1.4), which encode other kinds of information that is practically useful for test-case generation.

3.1.1 Type Annotations. A type annotation follows the syntax @arg(v):T, where v is a function argument (parameter), and T is a type constraint that specifies a set of possible values for v. A type annotation refers to the function that immediately follows it in the source code. A function can have up to as many type annotations as it has arguments.

AN supports several different type constraints, which can express a broad range of constraints—from simple ones, such as those that are also expressible using Python’s type hints, up to complex instances of special-purpose classes. The simplest, and most specific, type constraint uses keyword froms 6 to enumerate a list of valid values. For example, constraint froms([0, 0.0, None, zero()]) corresponds to any of the four values: integer zero, floating-point zero, None, and what is returned by the call zero().

Constraints for atomic types specify that an argument is a Boolean (bools), an integer number (ints), or a floating-point number (floats). Integer arguments can be restricted to a range between min and max values; for example, Lst. 2’s line 7 constrains nb_classes to be an integer between 2 and 22. Floating-point arguments can also be restricted to ranges, and the ranges can be open, closed, or half-open; for example, Lst. 2’s line 10 constrains compression to be a number in the half-open interval (0, 1] which includes 1 but excludes 0. Floating-point constraints also support including or excluding the special values NaN and Inf, as well as the precision (in bits) of the generated floating point values.

Constraints for sequences specify that arguments are Python lists, tuples, or an array in the NumPy library (which is widely used in NN programs, as well as other data-intensive applications). Lists and tuples can have any number of elements, whose possible values are also constrained using AN’s type constraints. For example, Lst. 2’s line 2 specifies a tuple with 3 integer elements: the first and second one between 20 and 70, and the third one between 1 and 3. AN also includes shorthands for lists with homogeneous elements: Lst. 2’s line 5 uses shorthand int_lists to specify lists of length between 2 and 5, whose elements are integers between 2 and 5.

The shape of a NumPy array is a tuple of positive integers that characterize its size. For example, the tuple (256, 256, 3) is the shape of a 3-dimensional array whose first two dimensions have size 256 and whose last dimension has size 3; arrays with this shape can represent 256x256 pixel color pictures. Type constraint np_shapes specifies arguments that represent shapes with a certain range of possible dimensions and sizes. For example, np_shapes(min_dims=3, max_dims=3) are the shapes of all 3-dimensional arrays whose dimensions can have any size.

Type constraint np_arrays specifies NumPy array arguments with any shape and whose elements have any of the valid NumPy types. The shape can be constrained by an np_shapes annotation or given directly as a tuple. For example, using the shape mentioned in the previous paragraph, np_arrays(np.type=type("uint32"), shape=(256, 256, 3)) specifies 256x256x3 arrays whose components are unsigned 32-bit integers (one of NumPy’s data-types), which could represent random color pictures.

Type constraints for maps specify Python’s widely used associative dictionaries: dicts(K, V, min_size, max_size) corresponds to all subsets of the Cartesian product K x V with between min.size and max.size elements, where K and V are type constraints that apply to the keys and values respectively. A typical usage of this is to constrain Python’s optional keyword argument **kwargs. For example, Lst. 3 shows how we used dicts to constrain the **kwargs argument of function dim.ordering.reshape (from a project using NN models to simulate multi-player games), so that it simply consists of all mappings from string "input_shape" to singletons representing the shapes of monodimensional arrays.

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Listing 3: An example of AN annotations for a function with keyword arguments.

```
1 @arg(k): ints(min=1, max=1000)
2 @arg(x): ints(min=1, max=1000)
3 @arg(kwargs): dicts(kys=froms(["input_shape"]),
4 values=np_shapes(min_dims=1, max_dims=1))
5 def dim.ordering.reshape(k, **kwargs):
```

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1 AN type constraints use names that are “pseudo-plurals” (by adding a trailing s) of the corresponding Python types. This avoids using reserved keywords and also conveys the idea that a type constraint identifies a set of values. This convention is also customary in property-based testing [6].

6 ANNoTest supports several different type constraints, which can express a broad range of constraints—from simple ones, such as those that are also expressible using Python’s type hints, up to complex instances of special-purpose classes. The simplest, and most specific, type constraint uses keyword froms to enumerate a list of valid values. For example, constraint froms([0, 0.0, None, zero()]) corresponds to any of the four values: integer zero, floating-point zero, None, and what is returned by the call zero().
To express the unions of several type constraints, AN includes the **any** type constraint, which specifies the union of its arguments. For example, Lst. 2’s line 5 says that dense_layers can be any of: (a) the number – 1, (b) an integer between 1 and 5, or (c) an integer list with between 2 and 5 elements that are between 2 and 5.

3.1.2 Custom Generators. While AN’s type annotations can define a broad range of frequently used constraints, they cannot cover all cases that one may encounter in practice. To support arbitrary type constraints, AN includes the **objs** annotation. This is used as a type constraint, and identifies all values that are produced by the user-provided **generator** function gen. Function gen must be visible at the entry of the functions whose annotations refer to it; gen itself is marked with the annotation @generator. In addition to providing this extension mechanism, we also equipped AN with several predefined generators that are useful to specify complex input objects that are frequently used in NN programs.

For instance, Lst. 4 shows the annotations we wrote for function build_gan8 (from the same project as Lst. 3). The function inputs two Keras model instances, generator and discriminator, and combines them to build GANs (Generative Adversarial Networks [9]). These instances are complex objects that are built by calls to the Keras library; therefore, we introduced two custom generators gan_gen and gan_disc to construct such instances for testing build_gan. Lst. 4 also shows gan_gen’s implementation: the generator’s input is constrained by using AN’s type annotations as usual; ANNoTest will use gan_gen’s output as input for build_gan. Generator gan_gen may look daunting to write; however, it simply follows and generalizes portions of the same tested project that build inputs for build_gan.

3.1.3 Preconditions. Argument annotations constrain each function argument individually. **Preconditions** express constraints that affect multiple arguments simultaneously: @require(P), where P is a Python Boolean expression, specifies that a function’s arguments

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Listing 4: An example of using type constraint **objs** and custom generator functions.

```python
1 def build_gan(generator, discriminator, name="gan"): 2 # ... 3 generator 4 discriminator 5 def build_gan(generator, discriminator, name="gan"): 6 # ... 7 generator 8 discriminator 9 def build_gan(generator, discriminator, name="gan"): 10 def build_gan(generator, discriminator, name="gan"): 11 def build_gan(generator, discriminator, name="gan"): 12 def build_gan(generator, discriminator, name="gan"): 13 def build_gan(generator, discriminator, name="gan"): 14 def build_gan(generator, discriminator, name="gan"): 15 def build_gan(generator, discriminator, name="gan"): 16 def build_gan(generator, discriminator, name="gan"): 17 def build_gan(generator, discriminator, name="gan"): 18 def build_gan(generator, discriminator, name="gan"): 19 def build_gan(generator, discriminator, name="gan"): 20 def build_gan(generator, discriminator, name="gan"): 21 def build_gan(generator, discriminator, name="gan"): 22 def build_gan(generator, discriminator, name="gan"): 23 def build_gan(generator, discriminator, name="gan"): 24 def build_gan(generator, discriminator, name="gan"): 25 def build_gan(generator, discriminator, name="gan"): 26 def build_gan(generator, discriminator, name="gan"): 27 return model
```

Listing 5: An example of using the **cc_example** auxiliary annotation on the constructor of class ImageGridCallback.

```python
1 @cc_example("image1.png", "image2.png", "image3.png", "image4.png") 2 @cc_example("image1.png", "image2.png", "image3.png", "image4.png") 3 @cc_example("image1.png", "image2.png", "image3.png", "image4.png") 4 @cc_example("image1.png", "image2.png", "image3.png", "image4.png") 5 @cc_example("image1.png", "image2.png", "image3.png", "image4.png") 6 @cc_example("image1.png", "image2.png", "image3.png", "image4.png") 7 # ... 8
```

3.1.4 Auxiliary Annotations. The AN language includes a few more features to control the test-generation process. Functions marked with @exclude are not tested (such as generator.gens in Lst. 4). Annotation @timeout introduces a timeout to the unit tests generated for the function it refers to.

Python modules may include snippets of code that is not inside any functions or methods but belongs to an implicit "main" environment. ANNoTest will generate tests for this environment for any module that is annotated with @module_test. Since modules don’t have arguments, these tests simply import and execute the main environment. This is a simple feature, but practically useful since some of the NN program bugs that were surveyed [13] are located in the main environment.

In order to test an instance method m, one needs to first generate an instance o of m’s class C to use as target of the call to m. To this end, C’s constructor is called to instantiate C. The constructor may also be equipped with AN annotations; as a result, testing m entails also fully testing C’s constructor. This can be a problem if the constructor has bugs that prevent a correct execution of m. To handle this scenario, AN includes the annotation @cc_example, which applies to a constructor and supplies a list of concrete inputs for it. If C’s constructor is equipped with this annotation, ANNoTest will only call it using the inputs given by the @cc_example annotation when it needs to create instances to test any methods of C. This way, one can effectively decouple testing a class’s constructor from testing the class’s (regular) methods, so that any bugs in the former do not prevent testing of the latter. For example, the constructor of class ImageGridCallback9 shown in Lst. 5 is regularly tested through its type annotations; however, when it is used to construct instances of the class to test other methods, it is only called with the more restricted set of inputs specified by the @cc_example annotation. The example also demonstrates that a generator function (grids in this case) can also be used as a regular function (second component of @cc_example).

3.2 Annotation Guidelines

To test a NN program using ANNoTest, one must first annotate the functions to be tested using the language described in Sec. 3.1.

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8It is just a coincidence that one argument is also named “generator”. 9It is just a coincidence that one argument is also named “generator”. 10It is just a coincidence that one argument is also named “generator”. 11It is just a coincidence that one argument is also named “generator”. 12It is just a coincidence that one argument is also named “generator”. 13It is just a coincidence that one argument is also named “generator".

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Listing 5: An example of using the cc_example auxiliary annotation on the constructor of class ImageGridCallback.
Ultimately, writing suitable annotations requires knowledge about the program’s specification—that is, its intended behavior. Many of the NN programs we used in Sec. 4’s experiments are sparsely documented and, even when some documentation is available, it is typically in natural language form (for example, Python’s doc-strings); therefore, distilling this information into AN annotations is a process that cannot be completely automated. To help such a process of “discovery”—to figure out suitable annotations for NN programs—and to make it cost-effective, this section presents some simple guidelines that suggest which artifacts to inspect and in which order. In the experiments described in Sec. 4, we followed these guidelines to annotate NN projects systematically and with reasonable effort.

Consider a Python function f in some NN project P that we would like to test. If f’s behavior (and, in particular, the constraints on its inputs) is documented in the project, this documentation should be the first source of information to write AN annotations. However, if f lacks any (precise) documentation, we will have to inspect its implementation. Tab. 1 lists four sources of information about f’s valid inputs in increasing level of detail.

To bootstrap the process, we inspect any usage of f within the NN program P. Since we focus on testing programs, not libraries, it’s very likely that every major function is called somewhere in P. These calls of f provide basic examples of valid inputs, which we can loosely encode using AN’s type annotations of Sec. 3.1.1. In Lst. 1’s example, looking at all usages of DenseNet’s constructor is enough to understand that input_shape should be a triple of int, compression should be a float, and so on.

Next, we look into f’s implementation for any (implicit or explicit) input validation. Often, a function raises some exception or introduces some assertions to signal invalid input arguments. This information is useful to refine the basic type annotations, and may also suggest constraint that involve multiple arguments—which we can encode using AN’s preconditions of Sec. 3.1.3. In Lst. 1’s example, DenseNet’s initial validation clearly indicates, among other things, compression’s precise interval of validity, and the precondition on line 13 in Lst. 2.

The library functions from some NN framework used in f’s implementation may also (indirectly) introduce requirements on f’s inputs or otherwise suggest plausible ranges of variability. Indirect constraints may be more complex to express, thus we may even have to introduce custom generators (Sec. 3.1.2). In the running example, a call to Keras’s Convolution2D constructor in DenseNet (not shown in Lst. 1) suggests the range for argument weight_decay at line 11 in Lst. 2.

Whenever f’s implementation calls other functions in the same project, this process has to be repeated for these other functions, while ensuring the consistency of theirs and f’s annotations. In the running example, DenseNet calls in a loop another function dense_block in the same project, passing growth_rate as argument and then incrementing it in each iteration. The input constraints of dense_block, once figured out, indirectly suggest the validity range for DenseNet’s growth_rate at line 6 in Lst. 2.

The guidelines we described are flexible and remain useful even if they are not followed in full. For example, sometimes we found it useful to start from very narrow annotations (merely encoding the available examples of usages of f in P) and relax them as we discovered more information—rather than going from basic to specific as we did in most examples—since this allowed us to generate some sample tests early on. The guidelines are also applicable with different levels of exhaustiveness, regardless of whether your goal is to annotate as much as possible in a project, or just test a few selected functions. In the former case, it is advisable to start annotating the simplest, shortest functions, so that their annotations can then suggest how to annotate the more complex, longer ones.

### 3.3 Test Generation

The annotations written in the AN language supply all the information that is needed to generate unit tests for every annotated function. In principle, we could use any technique for test-case generation and then filter any generated tests, keeping only those that comply with the annotations. Such an aimless strategy would however be very inefficient, especially given the dynamically typed nature of Python.

Instead, ANNoTest uses property-based test-case generation to actively match the constraints introduced by AN annotations. More precisely, the current implementation of ANNoTest uses the Hypothesis property-based test-case generator through its API. To test a Python function using Hypothesis, we have to write a test template, which consists of a parametric unit test method that calls a collection of strategies. A strategy is a sort of generator function, which outputs values of a certain kind. A parametric test method calls some of the strategies, combines their outputs, and uses them to call the function under test.

ANNoTest builds a suitable Hypothesis strategy for each @arg annotation. Hypothesis provides built-in strategies that cover basic type annotations, such as Python’s atomic types and tuples. ANNoTest reuses the built-in strategies whenever possible, and combines them to generate values for more complex or specialized constraints (such as int lists).

To encode arbitrary objs annotations (Sec. 3.1.2), ANNoTest first builds strategies for the annotations of each user-written custom generator function, as if it was testing the generator; then, it combines them to build a new strategy that follows the generator’s implementation to output the actual generated objects—used as inputs for the function under test.

To encode @require annotations (preconditions), ANNoTest uses Hypothesis’s assume function. When test-case generation reaches...
an assume, it checks whether its Boolean argument evaluates to true; if it does, generation continues as usual; if it does not, the current test input is discarded, and the process restarts with a new test. Thus, assumes can effectively act as filters to further discriminate between test inputs—a feature that ANNoTest leverages to enforce precondition constraints where appropriate in a parametric test.

After translating the annotations into suitable test templates, ANNoTest simply runs Hypothesis on those templates. The property-based test-case generator "runs" the templates to build unit tests that satisfy the encoded properties; it also runs these unit tests, and reports any failure to the user. Hypothesis's output is also ANNoTest's final output to the user.

3.4 Failing Tests and Oracles

The ANNoTest approach, and the AN annotation language on which it is based, works independent of how a test is classified as failing or passing. In other words, ANNoTest generates test inputs that are consistent with the annotations; determining whether the resulting program behavior is correct requires an oracle [3]. In this paper, we only ran the tests generated by ANNoTest with crashing oracles: an execution is failing when it cannot terminate normally; that is it leads to an assertion violation, an unhandled exception, or some other low-level abrupt termination.

While crashing bugs are the most frequent ones, NN programs also exhibit other kinds of bugs such as performance loss, data corruption, and incorrect output [13]. In principle, if we equipped the NN programs with oracles suitable to detect such kinds of bugs, ANNoTest could still be used to generate test inputs. However, some of these bug categories may be easier to identify by testing a NN at a different level than the bare program code. For example, bugs that lead to poor robustness of a NN classifier involve testing a fitted model rather than the model’s implementation [10, 20, 23]. Revisiting the ANNoTest approach to make it applicable to different kinds of oracles belongs to future work.

4 EXPERIMENTAL EVALUATION

The experimental evaluation aims at determining whether the ANNoTest approach is effective at detecting bugs in NN programs, and whether it requires a reasonable annotation effort. Precisely, we address the following research questions:

RQ1. Does ANNoTest generate tests that expose bugs with few false positives (invalid tests)?

RQ2. Can ANNoTest reproduce known bugs (that were discovered by manual analysis)?

RQ3. How many annotations does ANNoTest need to be effective?

4.1 Experimental Subjects

To include a broad variety of significant NN projects, we selected our experimental subjects following [13]'s extensive survey of NN bugs and their publicly available replication package, 10 which collects hundreds of NN program bugs from Stack Overflow posts and public GitHub projects. The former are unsuitable to evaluate ANNoTest, since they usually consist of short, often incomplete, snippets of code that punctuate a natural-language text. In contrast, the GitHub projects analyzed by the survey provide useful subjects for our evaluation. The survey [13] lists 557 bugs in 127 GitHub projects using the NN frameworks Keras, TensorFlow, PyTorch, Theano, and Caffe. With 350 bugs in 42 projects, Keras is the most popular project in this list; therefore, we target it for the bulk of our evaluation.

Starting from all 42 Keras projects, we excluded: (a) 3 projects that were no longer publicly available; (b) 7 projects with no bugs classified as "crashing" (see Sec. 3.4); (c) and 5 projects that still use Python 2. While it could be modified to run with Python 2, we developed ANNoTest primarily for Python 3, which is the only supported major version of the language at the time of writing. We excluded another 4 projects whose repositories were missing some components necessary to execute them (such as data necessary to train or test the NN model, or to otherwise run the NN program). Finally, 7 projects did not include any reproducible crashing bugs (see Sec. 4.2 for how we determined these). This left 16 projects using Keras, which we selected for our evaluation.

We focus on Keras since it is one of the most widely used NN frameworks. However, to demonstrate that ANNoTest is applicable also to other NN frameworks, we also selected 2 projects based on TensorFlow and 1 project based on PyTorch; these are among the largest projects using those frameworks analyzed in [13]. The leftmost columns of Tab. 3 list all 19 projects used in our evaluation, and their size in lines of code and number of functions.

4.2 Experimental Setup

This section describes how we setup each project before applying ANNoTest; and the experiments we conducted to answer the RQs.

4.2.1 Project Setup. As first step, we created an Anaconda11 environment for each project to configure and run it independent of the others. Every project has dependencies that involve specific libraries. Collecting all required dependencies can be tricky: a project may work only with certain library versions, older versions of a library may no longer be available, and newer backward-compatible versions may conflict with other dependencies. A handful of projects detail the specific versions of the libraries they need in a setup.py, requirements.txt, or Jupiter Notebook file—or at least in a human-readable readme. In many cases, none of these were available, so we had to follow a trial-and-error process: (a) search the source code for import statements; (b) retrieve the version of library L that was up-to-date around the time of the project’s analyzed commit; (c) in case that version is no longer available or conflicts with other libraries, try a slightly more recent or slightly older version of L.

NN programs usually need datasets to run. When a suitable dataset was not available in a project’s repository, we inspected the source code and its comments to find references to public datasets that could be used, fetched them, and added them to the project’s environment. In a few cases, the project included functions to generate a sample dataset, which was usually suitable to be able to at least test the project. For a few projects using very large datasets, we shrank them by removing some data points so that certain parts of the project’s code ran more efficiently. Whenever we did this, we ascertained that using the modified dataset did not affect general program behavior in terms of reachability—which is what matters for detecting the crashing bugs that we target in our evaluation.
To ensure testability, we added ...init... .py files to a project's directories, so that the test modules can import the program modules. In some projects, we moved some `import` statements from a class or function to the top-level module, so that the test modules get access to all the imported libraries just by importing the program's main module. Here too, we ensured that these changes did not affect the correct functioning of the project.

Properly setting up all NN programs so that they can be automatically run and tested was quite time-consuming at times, since several of the projects' repositories are incomplete, outdated, and poorly documented. Our replication package includes all required dependencies, which can help support future work in this area.

4.2.2 Experimental Process. To address RQ1, we selected the latest versions of two projects among the largest and most popular ones (ADV and GANS in Tab. 2) and followed the guidelines described in Sec. 3.2 to fully annotate them with \( \text{ANN} \). "Fully annotate" means that we tried to annotate every function of the project's source code, and to write annotations that are as accurate as possible: neither unnecessarily constraining (skipping some valid inputs) nor too weak (allowing invalid inputs).

To address RQ2, we tried to use \( \text{ANNoTest} \) to reproduce the bugs reported by [13] for the selected projects. More precisely, [13]'s companion dataset identifies each bug \( b \) by a triple \( (t, b^-, b^+) \): line \( t \) in commit \( b^- \) is the faulty statement, which is fixed by the (later) commit \( b^+ \). As we mentioned above, [13]'s dataset was collected by manual analysis, and thus some of the bugs are not (no longer) reproducible, are duplicate, or are otherwise outside \( \text{ANNoTest} \)'s scope. For our evaluation, we selected only unique reproducible crashing bugs: (a) "crashing" means that the fault triggers a runtime program failure, which we use as oracle;\(^4\) the crashing location \( c \) may be different from the bug location \( t \); (b) "reproducible" means that we could manually run the program to trigger the failure; (c) "unique" means that we merged bugs that are indistinguishable by a crashing oracle (for example, they crash at the same program point, or they fail the same assertion) or that refer to the very same triple in [13]'s dataset.

Out of all 213 bugs in [13] for the 19 selected projects, we identified 81 unique reproducible crashing bugs. For each such bug \( b = (t, c, b^-, b^+) \) we annotated the project's commit \( b^- \) starting from the function (or method) \( t \) where location \( t \) is, and continuing with the other functions that depend on \( t \). We stopped annotating as soon as the annotations where sufficient to exercise function \( t \) (including, in particular, reaching \( t \) and/or crash location \( c \)). Then, we ran \( \text{ANNoTest} \) to generate tests for \( t \) and any other functions that we annotated. We count bug \( b \) as reproduced if some of the generated tests fails at crashing location \( c \), and doesn’t fail if run on the patched version \( b^+ \).

4.3 Experimental Results

4.3.1 RQ1: Precision. Tab. 2 shows the results of applying \( \text{ANNoTest} \) to the latest commits\(^5\) of projects ADV and GANS. With the goal of annotating the projects as thoroughly as possible, we ended up writing some \( \text{AN} \) annotations for 42% of their 249 functions. Most of the functions that we left without annotations do not need any special constraints to be tested—usually because they are simple utility functions that are only called in specific ways by the rest of the project or have no arguments. There are a few additional cases of functions that are not used anywhere in the project and whose intended usage we could not figure out in any other way; in these cases, we did not annotate them (and excluded them from testing). With these annotations, \( \text{ANNoTest} \) reported 56 crashes, 50 of which we confirmed as genuine unique crashing bugs; this corresponds to a precision of 89%.

As previously reported [22], bugs due to project dependency conflicts are quite common in NN programs. An interesting example is a crash that occurs in ADV when it accesses attribute \( y^1 \) in Keras's class `Dense`.\(^13\) This attribute was renamed to `kernel` in Keras version 2.0. Since ADV explicitly supports this major version of Keras, this crash is a true positive. Another confirmed bug we found was due to a function in ADV still using tuple parameter unpacking—a Python 2 feature removed in Python 3. The ADV project developers probably forgot to update this one instance consistently with how they updated the rest of the project,\(^16\) which is indeed designed to work with Python 3.

A tricky example of false positive occurred in project GANS's function `create_celeba_channel_last`\(^17\) which creates an HDF5 file for the CelebA dataset\(^15\). One of the tests generated by \( \text{ANNoTest} \) crashes\(^19\) as it is unable to create a file. However, the failure does not happen if we run the function manually using the very same inputs; thus, the testing environment is responsible for the spurious failure.

These experiments suggest that \( \text{ANNoTest} \) can be quite effective to pin down bugs, problems, and inconsistencies in NN programs, thus helping systematically improving their correctness and reliability.

4.3.2 RQ2: Recall. Tab. 3 shows the results of applying \( \text{ANNoTest} \) to detect 81 unique reproducible crashing bugs in 19 projects surveyed by [13] and selected as explained in Sec. 4.1. Using the annotations we provided, \( \text{ANNoTest} \) reproduced 63 of these bugs without generating any spurious failing tests. This corresponds to a 100% precision and 78% recall relative to the unique reproducible known bugs from [13]. With the same annotations, \( \text{ANNoTest} \) also revealed another 31 failures that we confirmed as additional crashing bugs in the same projects.

While \( \text{ANNoTest} \) was quite effective at reproducing the known bugs in these projects, it’s interesting to discuss the issues that prevented it from achieving 100% recall. We identified several scenarios.

Masking occurs when an earlier crash prevents program execution from reaching the location of another bug \( b^' \). Masking is usually not a problem when the earlier crash is determined by a known bug \( b \); in this case, we can just run tests on the project commit \( b^- \) where \( b \) has been fixed, so that execution can reach the other bug \( b^' \). However, if a bug \( b^' \) is masked by an unknown bug (column

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\(^4\)While [13] classifies some bugs as "crashing", we also included bugs in other categories provided they can eventually generate a crash.

\(^5\)The projects are however no longer maintained; therefore, we did not submit any of the found bugs to the projects' repositories.

\(^6\)[13]'s survey is not meant to be an exhaustive catalog of all bugs in these projects.
Table 2: Two projects fully annotated with ANNoTest and the found bugs. Each row shows data about a project (identified by an acronym; see Tab. 3 for the URL of their GitHub repositories): its size in lines of code `loc` and number of `functions` (including methods); the average (per function) number `#A` of annotations we added to the project, the percentage `%F` of functions with at least one annotation, and the percentage `%G` of annotations that use custom generators; and the number of unique crashing bugs found by generating tests based on the templates—split into confirmed `true` bugs, `spurious` bugs (triggered by invalid inputs), and the corresponding `precision = true / (true + spurious)`.

| PROJECT | LOC | FUNCTIONS | ANNOTATIONS | BUGS |
|---------|-----|-----------|-------------|------|
|         |     |          | #A %F %G   | TRUE SPURIOUS PRECISION |
| ADV     | 1421| 100      | 1.58 49% 7%| 33 5 87% |
| GANS    | 2496| 149      | 1.15 37% 6%| 17 1 94% |
| overall | 3917| 249      | 1.33 42% 7%| 50 6 89% |

Table 3: Bugs from [13] that ANNoTest could reproduce. Each row shows data about a project (identified by an acronym and the URL of its GitHub repository): its DNN framework (Keras, TensorFlow, Torch), its size in lines of code `loc` and the number of total and tested `functions` (including methods); the number of its different `rev` ersions that we analyzed, the average (per tested function) number `#A` of annotations we added, the percentage `%F` of functions with at least one annotation, and the percentage `%G` of annotations that use custom generators; and the number of crashing `bugs` found by generating tests based on the templates—the number of reproducible `known` bugs reported in [13], how many of these the tests reproduced, how many `other` confirmed true bugs and `spurious` bugs (triggered by invalid inputs) the tests also reported in the same experiments, and the corresponding `precision = (rep + others) / (rep + others + spurious)` and `recall = rep / known`.

| PROJECT | LOC | FUNCTIONS | ANNOTATIONS | BUGS |
|---------|-----|-----------|-------------|------|
|         |     |           | #A %F %G   | TRUE SPURIOUS PRECISION |
| K NAAS  | 140 | 7         | 0 0% 0%    | 2 2 0 100% 100% |
| K ADV   | 1421| 100       | 4 1.5 4%   | 8 6 3 0 100% 75% |
| K DN    | 82  | 5         | 2 1.4 40% 0%| 2 2 0 100% 100% |
| K DCF   | 748 | 35        | 1 4 3% 0%  | 1 0 0 0 0% 0% |
| K KIS   | 2050| 92        | 2 1.5 2% 0%| 6 5 0 0 100% 83% |
| K FRCNN | 35  | 20        | 0 0% 0%    | 1 1 0 0 0% 0% |
| K CONV  | 50  | 20        | 0 0% 0%    | 1 1 0 0 0% 0% |
| K mCRNN | 225 | 1         | 0 0% 0%    | 1 1 0 0 100% 100% |
| K IR    | 306 | 38        | 0 0% 0%    | 2 0 0 0 0% 0% |
| K RE    | 966 | 25        | 1 1 15.0 4%0%| 1 1 5 0 100% 100% |
| K CAR   | 353 | 21        | 1 7.0 5% 0%| 1 1 1 0 100% 100% |
| K GANS  | 2496| 149       | 2 1.25 1% 4%| 6 4 5 0 100% 67% |
| K KAX   | 227 | 15        | 0 0% 0%    | 1 0 0 0 0% 0% |
| K VSA   | 630 | 38        | 2 1 6.0 5% 0%| 2 2 4 0 100% 100% |
| K UN    | 440 | 28        | 3 2 3.3 11% 30%| 6 2 1 0 100% 33% |
| K LSTM  | 477 | 27        | 0 0% 0%    | 1 0 0 0 0% 0% |
| F TC    | 285 | 7         | 0 0% 0%    | 9 9 2 0 100% 100% |
| F TPS   | 286 | 2         | 2 1 4.0 100% 87%| 24 24 0 0 100% 100% |
| T DAF   | 1094| 70        | 1 1 9.0 1% 67%| 1 1 2 0 100% 100% |
| overall | 14219| 735       | 24 23 6.0 3% 12%| 81 63 31 0 100% 78% |

other in Tab. 3), and we don’t know how to fix the unknown bug to allow the program to continue, $b'$ is effectively unreachable. We could not reproduce 4 known bugs because of masking. One of them occurs in project GANS, and is masked by an unexpected crash occurring in the same function `Discriminator`.

ANNoTest generates unit tests, which target specific functions in a program's source code. This excludes any code snippets in the "main" section of a Python file (under `if __name__=='__main__'`), which executes when the file is run as a script from the command line. Therefore, ANNoTest could not reproduce 6 bugs affecting this scripting code, such as one known bug in project CONV. Another example is the only known bug in project KAX, which occurs in a function that depends on command line arguments.

ANNoTest can test nested functions only indirectly, that is when they are called by a top-level function as part of testing the latter. It does not support annotating nested functions and generating unit tests for them. We could not reproduce 3 known bugs because they affected nested functions. An example is in project FRCNN's...
work a rigorous empirical evaluation of the time and expertise that [Tab. 2], we wrote
This scenario occurred for 3 known bugs that
annotated the projects, we would have likely amortized some of this
slightly modified from one experiment to the other. If we had fully
bug; therefore, several of the annotations are duplicated or only
portion of a project focusing on a specific function that had a known
in Tab. 3 since in each of those experiment we annotated a limited
average number of annotations per tested function is higher (6.0)
only a handful of functions required more than 4 annotations. The
distribution of annotations per function in Fig. 2 further shows that
limited. In the experiments where we fully annotated two projects
ANNoTest’s unit testing environment (or rather its Hypothesis
back-end’s). We could not reproduce 1 known bug44 in project KIS
because it uses yield to build a lazy iterator.
As we remarked above, a bug’s crashing location c may differ
from the actual error location ℓ in commit b−. If c is in a portion of
the code that is not accessible to the testing environment, ANNoTest
cannot reproduce the bug even if it is reproducible in principle.
This scenario occurred for 3 known bugs that ANNoTest didn’t
reproduce. Two of them are in project UN45,46 and only crash in
a module whose implementation is incomplete in that program
revision. Another one47 occurs in project IR: we tried to no avail to
reproduce it at a different, accessible location.
Finally, we could not reproduce 1 bug48 in project IR simply
because we could not figure out suitable type constraints to properly
exercise the corresponding function.

Figure 2: Distribution of the number of AN annotations for
the functions in projects ADV and GANS in Tab. 2.

function rpn_loss_regr_fixed_num,43 which is defined inside top-
level function rpn_loss_regr.
Functions using Python’s yield statement are lazy, that is their
evaluation is delayed. This means that they may not be executed by
ANNoTest’s unit testing environment (or rather its Hypothesis back-end’s). We could not reproduce 1 known bug44 in project KIS
because it uses yield to build a lazy iterator.
As we remarked above, a bug’s crashing location c may differ
from the actual error location ℓ in commit b−. If c is in a portion of
the code that is not accessible to the testing environment, ANNoTest
cannot reproduce the bug even if it is reproducible in principle.
This scenario occurred for 3 known bugs that ANNoTest didn’t
reproduce. Two of them are in project UN45,46 and only crash in
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revision. Another one47 occurs in project IR: we tried to no avail to
reproduce it at a different, accessible location.
Finally, we could not reproduce 1 bug48 in project IR simply
because we could not figure out suitable type constraints to properly
exercise the corresponding function.

4.3.3 RQ3: Annotation Effort. For the ANNoTest approach to be
practical, it is important that the effort required to manually anno-
tate functions is reasonable and cost-effective. We leave to future
work a rigorous empirical evaluation of the time and expertise that
is needed to write AN annotations. Here, we measure the effort in
terms of output—that is the written annotations—and discuss some
qualitative findings.
The amount of annotations that we had to write was generally
limited. In the experiments where we fully annotated two projects
(Tab. 2), we wrote 1.33 annotations per function on average. The
full distribution of annotations per function in Fig. 2 further shows that
only a handful of functions required more than 4 annotations. The
average number of annotations per tested function is higher (6.0)
in Tab. 3 since in each of those experiment we annotated a limited
portion of a project focusing on a specific function that had a known
bug; therefore, several of the annotations are duplicated or only
slightly modified from one experiment to the other. If we had fully
annotated the projects, we would have likely amortized some of this
annotation effort. Another way of quantifying the effort-benefit
trade-off is measuring the amount of annotations per detected
bugs: this ratio is 6.6 = 330/50 for the fully-annotated projects in
Tab. 2 and 1.5 = 145/94 for the experiments in Tab. 3. These are
encouraging figures, if we think of the amount of manually-written
tests that may have been necessary to discover the same bugs.
As seen in the examples of Sec. 2, AN annotations are usually con-
cise and encode simple information. The exception are annotations
using generators (Sec. 3.1.2), which require to write custom func-
tions that build instances of a complex type. However, only 7% (22)
of all 330 annotations written for projects ADV and GANS in Tab. 2
use a generator. The percentage of annotations using generators is
higher (12%) for the projects in Tab. 3; as for regular annotations,
the effort remained manageable since there was reuse involved
between experiments targeting different bugs in the same project.
The most common situations that required custom generators was
generating NN models, such as Keras models or TensorFlow ten-
sors; 71% of all custom generators (including the example in Lst. 4)
perform these tasks. Other generators that we wrote deserialized
some data from disk and dispatch them as inputs. Neither kind
of generator is really project-specific, although generation of NN
models is framework-specific. As future work, we might extend AN
to support the definition of framework-specific models.

| In experiments with fully-annotated NN programs, ANNoTest used 1.33 annotations per function on average. Only 7% of them involved writing custom generators. |

| ANNoTest generated tests revealing 63 known NN bugs in 19 NN programs, with a recall of 78%. |

4.4 Threats to Validity

Identifying valid test inputs, and distinguishing between spurious
and authentic bugs, is crucial to ensure construct validity (i.e., the
experimental measures are adequate). Unfortunately, a reliable and
complete ground truth is not available: the documentation of NN
programs is often incomplete (when it exists), so we had to manually
discover the intended behavior of NN programs from examples,
manual code analysis, and background knowledge. Our reference—
Islam et al. [13]’s survey—was also compiled by purely manual
analysis; therefore, it does not aim at completeness, and includes
bugs that are not reproducible (see Sec. 4.2). These limitations imply
that we cannot make claims of completeness (“we found all bugs”);
nevertheless, we still have a good confidence in the correctness
of our results (“we found real bugs”): since we focused on bugs
detected by crashing oracles, most bugs we found with ANNoTest
are clear violations of the program’s requirements.

Since ANNoTest uses manually-written annotations, quantifying
the annotation effort is needed for internal validity (i.e., the experi-
mental results are suitable to support the findings). We mostly
reported simple measures (number of annotations, number of func-
tions that require annotations, etc.) which are unambiguous. In
contrast, we do not make any strong claims about the time and
relative effort needed by programmers to annotate: these heavily
depend on a programmer’s knowledge of the NN program and
of the domain; precisely assessing them would require controlled
experiments and user studies, which are outside this paper’s scope.

Picking experimental subjects from Islam et al. [13]’s extensive
survey helps external validity (i.e., the findings generalize). As we
discussed in Sec. 4.1, we excluded some projects for practical rea-
sons (e.g., no longer available or incomplete) and we focused on
those using the Keras NN framework. While this focus does not seem especially restrictive (the majority of projects in the survey uses Keras, and we also analyzed projects using other frameworks), applying ANNoTest to very different kinds of NN programs may require different kinds of annotations or other changes in the approach. The AN annotation language is extensible by writing custom generators (Sec. 3.1.2), which can further help generalizability.

5 RELATED WORK

Automated test-case generation. Since testing is a fundamental activity to ensure software quality [4], software engineering research has devised several different techniques to automate the generation of test inputs [2]. Randoop [18] (based on random testing) and EvoSuite [8] (based on genetic algorithms [1]) are two of the most popular tools for Java implementing automated test-case generation. Techniques such as those implemented by Randoop and Evosuite usually depend on the typing information about a method’s input that is provided statically in languages such as Java.

Test-case generation for Python. In contrast, programs written in dynamically typed languages like Python do not include such information, which complicates test-case generation. In fact, despite Python’s popularity [5], the first widely available tools for automated test-case generation in Python appeared only in recent years [16, 17]. Pygavin [16] is based on genetic algorithms like EvoSuite, and relies on Python’s type hints. Hypothesis [17] implements property-based testing, which generates random inputs trying to satisfy some programmer-written properties. ANNoTest is also an automated test-case generator for Python, but it provides a specialized set of expressive annotations useful to precisely express the valid inputs of NN programs. Then, it defers the actual test-input generation to Hypothesis, which it uses as back-end. With a different encoding, Pygavin could also be used as a back-end of ANNoTest (an experiment which we may try in future work). Directly using Pygavin or Hypothesis to generate tests for NN programs is possible in principle, but it would involve more manual work to express the necessary constraints indirectly through a combination of type hints (Pygavin), testing strategies (Hypothesis), or programmatically directly in Python.

Bugs in NN programs. Following the increasing in popularity of NN and other forms of machine learning (ML), some recent research has looked into the nature of bugs that occur in NN and ML programs to understand how they differ compared to “traditional” software. Thung et al. [24] studied bugs and human-written patches in 3 ML projects (Apache Mahout, Lucene, and OpenNLP) and classified them according to criteria such as bug severity and fixing effort. A similar study [22] of 3 other ML projects (Scikit-learn, Paddle, and Caffe) revealed that compatibility bugs due to conflicts between project dependencies are quite common in these programs—as they were in the subjects we used in Sec. 4’s experiments.

Zhang et al. [25]’s analysis of TensorFlow-based NN projects found that modeling mistakes, incorrect shape of input tensors, and unfamiliarity of users with TensorFlow’s computation model were among the most frequent origins of bugs. Once again, these findings set NN programs apart from traditional software. Recent studies by Islam et al. [13, 14] on 5 NN frameworks confirmed some of [25]’s findings and further found that bug fix patterns in NN programs are often different compared to traditional programs. In the same line of research, Humbatova et al. [12]’s extensive taxonomy of bugs in deep learning systems identified several causes of bugs that are specific to NN program, including incorrect/incomplete models, wrong input data types, and training process issues.

Bugs in NN models. As we recalled in Sec. 1, a NN program implements in code a NN model that is trained on some data, both of which can also be plagued by mistakes. Hence, traditional software engineering approaches to test generation [23], mutation testing [10, 20], fault localization [7], and even automated program repair [21] have been applied to NN models and training data to assess and improve their quality, robustness, and correctness. Under this paradigm, bugs are revealed by adversarial examples, e.g., two slightly different inputs that appear identical to the human eye but result in widely different classification by a trained model [23]. Adversarial examples correspond to failing tests; and fault localization and fixing correspond to finding [7] and changing [21] neuron weights in a model. This kind of research is complementary to our work on ANNoTest, which is specific to NN programs but focuses on testing and finding faults in their code implementations.

6 CONCLUSIONS

The paper presented the ANNoTest approach to generate inputs that test NN programs written in Python. ANNoTest relies on code annotations that precisely and succinctly describe the range of valid inputs for the functions under test. Using this information, ANNoTest can generate tests that avoid spurious failures, and thus have a good chance of exposing actual bugs. In an experimental evaluation targeting 19 open-source NN programs, ANNoTest was able to reveal 94 bugs (including 63 previously known ones) with an overhead of 6 annotations per tested function on average.

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