Transformation of Python Applications into Function-as-a-Service Deployments

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Abstract

New cloud programming and deployment models pose challenges to software application engineers who are looking, often in vain, for tools to automate any necessary code adaptation and transformation. Function-as-a-Service interfaces are particular non-trivial targets when considering that most cloud applications are implemented in non-functional languages. Among the most widely used of these languages is Python. This starting position calls for an automated approach to transform monolithic Python code into modular FaaS units by partially automated decomposition. Hence, this paper introduces and evaluates Lambada, a Python module to dynamically decompose, convert and deploy unmodified Python code into AWS Lambda functions. Beyond the tooling in the form of a measured open source prototype implementation, the paper contributes a description of the algorithms and code rewriting rules as blueprints for transformations of other scripting languages.

1 Introduction

Software application engineers are faced with an ever-growing choice of frameworks and programming interfaces. The issue is among the most daunting ones in contemporary service-oriented computing, namely in cloud platform services and web frameworks [1]. The undesirable effects are continuous breakage and growing obsolescence. Instead of continuously refactoring and rewriting the application without noticeable benefit to the end user, it is desirable to make use of automated transformations to new target platforms [2, 3]. Apart from model-driven architectures with targeted code generation, such solutions are also needed for existing code where any adaptation needs to be performed directly on the code level. This requirement applies in particular to most cloud
applications which are often developed in ad-hoc ways without formal engineering processes due to quickly evolving platform and infrastructure programming interfaces [4].

Application software engineering is in general a wide field divided into multiple popular design methodologies, programming models and languages for the generation and development of code, as well as heterogeneous target platforms, interaction patterns and runtime stacks. Many applications consist not only of code and data, but also of essential metadata which describes how the application integrates with its environment. In the cloud applications space, the velocity of change in the metadata space is very high. A few years back, it may have been sufficient to describe an application in terms of a monolithic virtual machine configuration. In many recent settings, both technical and non-technical characteristics of microservices need to be properly described, and the code and data needs to be deployed accordingly [5]. The recent introduction of Function-as-a-Service environments expands this path and thus presents a qualification barrier for most application engineers.

Indispensably, novel tools are needed to assist the engineers with guidance and automation to achieve live cloud service access to their applications. The focus of the paper is thus to explore the automated configuration, code transformation and deployment challenge specifically for applications implemented in Python and executed as a set of hosted functions. The choice of Python for the exploration is reasonable due to the language characteristics and its widespread use especially for cloud application development. The work shares similarities with automated transformation approaches for Java [6] but adds the perspective of dynamic code analysis and further unique characteristics due to the transparent bytecode compilation of Python code.

To analyse the issues, the next section deduces an initial research question and justifies incremental refinements to it. The resulting research question is then answered by first presenting the design of a transformation tool called Lambada. The design is followed by a description of the transformation process including applicable abstract syntax tree transformation rules. Subsequently, the implementation is described and measured and conclusions for future cloud application development are drawn.

2 Background and Research Question

Python as programming language for applications has been studied in various directions. The studies answer questions such as: how do Python programs use inheritance [7]; how do Python programs evolve over time through code changes [8]; how to accelerate Python programs with cloud resources [9]; how to offload Python program code from mobile applications to cloudlets [10]. Although some of the works relate to cloud infrastructure, they assume (and often introduce) specific programming interfaces and hardware resources which are present only in prototypical form and not in commercial offerings today. This limits their applicability to actual cloud target environments. To the author’s
knowledge, there are no studies which show how to systematically transform vanilla Python applications into deployment forms directly consumable by public cloud providers. Therefore, the general research question is how to prepare the code and configuration of Python software applications to allow for seamless deployment into the cloud, or in short: How are Python programs cloudified?

As cloud computing is a wide field with various programming and deployment models, this research concentrates on hosted functions as the one which has recently attracted a lot of attention due to cost benefits for function-sized microservices \[11\] and the influx of discrete data to be processed from sensors, smart cities and connected devices \[12\]. This Function-as-a-Service (FaaS) model gives application engineers a seemingly serverless interface. The process of automated translation of code into deployable function units is consequently called FaaSification. The research question then becomes more concrete: How are Python programs faasified?

For the scoping of the work, the paper further restricts the initial research to a single management and runtime interface of FaaS. In the absence of standards beyond single vendors, the interfaces correspond to those implemented by AWS Lambda, while allowing flexible endpoint changes to not be limited to AWS as provider. An additional requirement is the avoidance of any manual changes to the program source code as this could introduce new bugs and issues. A third requirement is that Python’s multi-paradigm nature is supported by translating both functions and methods on objects into function units. All three requirements contrast previous designs such as Briareus \[9\] and PyWren \[13\]. This leads to the specific research question:

How are mixed-paradigm Python programs lambdafied without requiring any modification?

Fig. 1 puts this narrowed research scope into context. The research question is placed on the central axis to the right side whereas possible alternative explorations are indicated as well.

3 Tool Design

The anticipated tool to automate the placement of Python code into Lambda is called Lambada, owing to the ambition to turn a complex series of steps into an
enjoyable activity. Lambada is designed as a non-intrusive tool which works with existing vanilla Python code and thus targets software engineers and developers without specialised qualifications concerning cloud computing. The principal goal is to run Python code through Lambada in order to execute it in the scalable, resilient and invocation-centric Lambda environment. To accommodate different use cases, the tool needs to be invocable from the command line (black box application) and from within Python code (grey box application). Loose coupling with the Lambda management (control plane) interface is achieved by not interfacing directly through a corresponding library (e.g. Boto), but instead relying on the default command-line utility (AWS CLI) including prior region and credentials configuration.

The Lambada tool dynamically imports the application code, inspects the namespace, and transforms functions and classes into local proxies paired with generated remote functions. Referenced module imports are inspected and their contents are transformed recursively. The subsequent processing depends on the chosen mode. In production mode, all remote functions are deployed upon first invocation and are later used directly, suggesting a slowdown for the first invocation. The main code block of the application is then executed with references to the remote functions. In debug mode, the generated and rewritten functions are instead serialised into local files and no execution takes place.

The design of the tool is influenced by the expected inputs and outputs. The inputs are assumed to be moderately complex Python applications consisting of a primary module and its dependency modules which contain mixed amounts of procedural (def) and object-oriented (class/def) code. All methods and functions have arbitrary parameter counts and types. The outputs are functions adhering to the Lambda signature of two parameters event and context in a function by default named lambda_handler.

Fig. 2 shows the anticipated tool design. The dashed parts are generated and/or injected into the application at runtime. The striked parts are deleted from the interpreter memory and thus removed from the execution.

The code transformation is based on function and class definitions on the input side. Each function and method is projected onto a single hosted function. While the code introspection happens dynamically, it is subject to static feasibility checks. Functions and methods containing legitimate bodies are admitted to the transformation independently from foreseeable execution issues due to
restrictions in the target environment. In AWS Lambda and many competitor services, these restrictions encompass both time (e.g. 300 seconds maximum duration) and space (e.g. 1.5 GB maximum allocation of RAM).

Lambada makes use of two output channels: Persistent local files for rewritten code, corresponding to debug mode, and ephemeral function unit files which are partially deployed into Lambda, corresponding to production mode. Fig. 3 shows the paths for transforming Lambda code including the input and output elements.

![Figure 3: Paths in the Lambada code transformator](image)

4 Transformation Process

Code transformation may refer to syntax changes on different levels. In CPython, the default interpreter for Python, source code is first tokenised (token/parser level), then assembled into an abstract syntax tree (tree level), and finally bytecode-compiled. Although other interpreters exist [14], access to the syntax tree is always possible at runtime. The code transformation in Lambada is performed with specific rules for Python modules, functions, classes and methods on the syntactic level. It also considers standard input and output adaptations to the hosted functions environment. There are two kinds of rules: direct manipulations of the abstract syntax tree, and code templates which are filled, compiled and inserted at appropriate nodes of the tree.

The rules apply to five major syntax elements: modules, functions, classes with methods, globals as well as called built-ins for standard input and output. These elements are described in the next paragraphs.

4.1 Modules

In Python, each script file represents a module which is loaded with the file name but omitting the .py suffix. To lambdafy an application, the set of modules belonging to this application needs to be determined. This can be accomplished on the file level by checking which files belong to a certain application project, or on the function level by recursive traversal of dependency functions. The second approach is more precise as it does not attempt to transform files with code paths unreachable from a certain function, but also requires more care to stop the traversal for modules outside of the application scope such as system modules. Another advantage is that it allows for dynamic analysis so that
modules which are imported conditionally, or based on evaluated code, will be
identified correctly. Lambada thus follows the second approach.

Fig. 4 gives an example of the traversal. On the left side, an application
consists of code which references a module called entrance module. Multiple
dependency modules are referenced from it, of which only some belong into the
application scope. On the right side, the transformed code is represented. As all
functions are transformed into corresponding Lambda units, their invocations
across module boundaries involve the Lambda runtime as gateway.

![Figure 4: Function dependency analysis across module boundaries](image)

### 4.2 Functions

The abstract syntax tree is recursively walked. Interceptions happen at func-
tion invocations (calls) and function definitions. A dependency map between
calling and called functions is continuously updated at each call interception.
The function analysis does not encompass inline anonymous functions which in
Python are, ironically, called Lambdas.

Code templates exist for remote function equivalents, local call stubs and
local replacements, as well as for function proxies for all dependencies. They
are instantiated and filled for each definition whereas calls are merely rewritten
to point to the call stubs instead. Furthermore, the remote function units are
packaged along with suitable configuration into archive files and deployed into
the target Lambda environment.

Fig. 5 gives an example of a function transformation. The original func-
tion which had a single local entrypoint is replicated unmodified or with slight
modifications and placed into the target environment which leads to a second
entrypoint. A local stub and a remote skeleton as parameter-compliant wrapper
function connect both environments.
4.3 Classes

The programming model of FaaS mandates functions. Classes therefore need to be decomposed into their methods which are then represented as stateless functions, receiving the object state for each invocation as additional parameter. One technique to do so is name mangling as known from linking C++ binary code [15]. Another technique is method call interception. It fits well into the anticipated generic programming model and is therefore the chosen technique which will be presented.

Two generic proxy classes, one on the service side and one on the client side, perform the exchange of function names, call arguments and associated object state. The client-side proxy is a metaclass which is instantiated into a derived class with a hidden attribute referring to the class to be replaced. Objects of this class then accept all attribute and method accessors as the substituted class. On the client side, all class definitions are dynamically overwitten with this proxy class.

On the service side, all class definitions are used almost unmodified. The only necessary change is the introduction of a separate constructor method (\texttt{\_\_remote\_\_init\_\_}) which can be intercepted similar to regular methods, and its invocation from the original constructor (\texttt{\_\_init\_\_}).

Method calls transmit the module name, class name, method arguments and a dictionary representation of all attributes.

Due to the limitation imposed by most FaaS models to only allow for a single entry-point function per file or set of files, the class definition needs to be duplicated as separate hosted function for each method.

4.4 Globals

In contrast to most compiled programming languages, the syntax of Python does not foresee a main function. The language’s equivalent of a main function in a module is the ordered set of all lines not part of a function or class definition. By convention, a stricter equivalent is marked as a conditional branch whose condition reads \texttt{if \_\_name\_\_ == "\_\_main\_\_"} and whose code block contains the function implementation. To make Lambada practical, such blocks are replicated verbatim in the local rewritten file.

Furthermore, global variables may be referenced by functions. While considered bad practice, this pattern is still common practice and hence is targeted by the transformation by placing a replicated global variable alongside each
affected deployed function. The use of such variables to synchronise state, for
instance through message queues, is therefore inhibited implicitly. Such changes
in programming semantics can only be discovered through subsequent unit test-
ing.

4.5 Input and Output

Lambada scans the syntax tree for any occurrence of input or print (output)
function calls per function. If the presence is detected, monads are set up to
carry any data input and output across invocations and across the network to
and from the caller. The print monad is a global variable which concatenates
all text and finally returns it as second return value next to the actual one to
the caller.

5 Implementation and Evaluation

Lambada is implemented as Python 3 executable module following the proposed
design. The code size is around 300 lines for handling functions and their trans-
formation and deployment and 100 lines for handling classes and methods, plus
20 lines for the application wrapping the module. These numbers exclude ex-
ternal modules for code generation (codegen) and any battery modules used
from the standard Python distribution. In the following, selected implementa-
tion details are presented before proceeding to the presentation of evaluation
results.

5.1 Proxy Classes

Listing 1 describes the implementation of the proxy class for transparent lambda-
fication of methods. Python’s __new__ method is therein called twice: first, to
return an object of the proxy class with a flag indicating it, and second, an
instance of the actual object wrapped into the proxy object. Subsequently, any
method or attribute access is handled by the proxy which transfers state be-
tween the local object and the lambda-side object, keeping both in sync for any
potentially stateful method invocation.

Listing 1: Proxy class implementation

class Proxy:
    def __new__(cls, classname, proxy=True):
        if proxy:
            return lambda: Proxy(classname, False)
        else:
            return object.__new__(cls)

    def __init__(self, classname, ignoreproxy):
        self.classname = classname
        self.__remote__init__()
5.2 Invocation

There are three different ways to invoke Lambada: as a command-line application, as an executable Python module, and as a regular Python module. For integration with development environments, for instance as part of continuous testing, integration and deployment chains, Lambada runs as standalone application targeting any files specified as command-line parameters. Only in this way Python scripts containing functions and methods can be rewritten locally. The pre-loaded module is a main program which is run before the application main program and hooks into all globals such as imported modules and function declarations. Being a module itself, Lambada can also be imported into the application to consciously and selectively transform parts of the application in case minimal code modifications are permitted.

In the first two cases, the target module is specified, whereas in the third case, the current execution context is assumed as starting point from which, in all three cases, imported modules are recursively transformed when demanded by function dependencies not part of the standard library which is also expected in the target environment. Furthermore, in all three cases, a custom endpoint can be specified in case the functions are intended to be uploaded not to AWS Lambda but to reimplementations thereof, such as Snake Functions [16].

5.3 Experimental Evaluation

The practical use of Lambada is evaluated empirically by transforming self-contained Python functions and applications and measuring both the transformation overhead and the resulting execution overhead. All results have been obtained on a Notebook running Linux 4.9.0 and Python 3.5.3 on an Intel i7-5600U CPU with 4 cores à 2.60 GHz. The network connection to AWS Lambda’s US-West-1 region is located on SWITCHlan, the 100 GBit/s Swiss research and education network, with an ICMP roundtrip time of 2 ms, jitter of 3 ms and effective transfer rates of 94 Mbps averaged during the experimental runs. All
Lambda instances have been configured as smallest with 128 MB of RAM which inherently influences the execution speed through an opaque mapping of memory allocation to CPU allocation within the service. The material to reproduce the experiment under similar or different conditions is available along with the Lambada implementation.

Table 1 describes a purely local example of a single recursive Fibonacci function $\text{fib}$ implemented in Python. The original implementation is lambdafied, rewritten to a local file copy, and locally executed with Lambda execution syntax and semantics including JSON serialisation. The function instance is parameterised with a value $x$, leading to a result of $y = \text{fib}(x)$ involving $2y - 1$ total function calls. The overhead per function invocation contains the constant time of $L = 67ms$ for the lambdafication process itself and is calculated as per Eq. 1.

\[
\text{overhead} = \frac{T_{\text{lambda}} + \frac{L}{2y-1}}{T_{\text{orig}}} - 1. \tag{1}
\]

The lambdafication overhead is extremely significant for functions which are invoked once and insignificant for functions invoked thousands of times. The lambdafied execution overhead is still highly significant independent of the number of invocations with a slowdown factor of around 100 mostly due to JSON parsing. It should be noted that by using the optimised Python interpreter PyPy instead of the standard CPython implementation, the absolute execution times are reduced to a varying level of around 45-70% and the overhead factor drops from around 100, where it stabilises for higher values of $x$, to around 67. These limits are representing the practical upper boundary of overhead as most functions would contain a higher share of computation. Another interesting observation is that $\text{fib}(30)$ would already exceed the free tier limit of 1 million function invocations at AWS Lambda. For completeness, the function source code is shown in Listing 2.

### Listing 2: Fibonacci function implementation

```python
def fib(x):
    if x in (1, 2):
        return 1
    return fib(x - 1) + fib(x - 2)
```

Table 1: Local Fibonacci comparison.

| Invocation | Calls | Original | Lambdafied | Overhead |
|------------|-------|----------|------------|----------|
| $\text{fib}(1)$ | 1 | 0.0003 ms | 0.0210 ms | 223402.33 |
| $\text{fib}(10)$ | 109 | 0.0202 ms | 1.3200 ms | 396.03 |
| $\text{fib}(20)$ | 13529 | 1.57 ms | 156.47 ms | 98.67 |
| $\text{fib}(30)$ | 1664079 | 191.81 ms | 19639.70 ms | 101.39 |
| $\text{fib}(40)$ | 204668309 | 24989.58 ms | 2382736.84 ms | 94.34 |
The second such function is an extended recursive Fibonacci function \texttt{fibs} which on each invocation calculates the invocation count’s number of sine values. This makes it more compute-intensive and less invocation-intensive, avoiding high experimentation cost while now including the deployment to and runtime at AWS Lambda as well. It is also a test case for handling global variables since the invocation count needs to be maintained persistently across invocations. The overhead per function invocation therefore includes two constants, the lambdafication process time (again \( L = 67\text{ms} \)) and the deployment time (network-dependent, around \( D = 4200\text{ms} \) on the test system), leading to a shared overhead part of \( \frac{L+D}{y-1} \). Table 2 compares the performance values for selected parameters averaged over 100 command-line invocations each. Due to the higher computation complexity, the parameter \( x \) is set to lower values compared to the previous run, although \texttt{fibs(1)} and \texttt{fibs(10)} are contained in both sets. Already with \texttt{fibs(19)} the Lambda instance will time out.

| Invocation | Calls | Original | Lambda | Overhead |
|------------|-------|----------|--------|----------|
| \texttt{fibs(1)} | 1 | 0.04 ms | 18.94 ms | 107147.49 |
| \texttt{fibs(10)} | 109 | 1.33 ms | 1157.77 ms | 898.94 |
| \texttt{fibs(12)} | 287 | 6.54 ms | 7041.89 ms | 1078.01 |
| \texttt{fibs(15)} | 1219 | 117.31 ms | 14857.44 ms | 125.68 |
| \texttt{fibs(18)} | 5167 | 2235.03 ms | 63893.69 ms | 27.59 |

The observations are remarkable. First, there is a slowdown factor in the order of magnitude of significantly less than 100 for invocations with longer compute periods despite including the network deployment. This makes a number of real-world use cases without strict latency requirements possible. Second, the invocation time variance is much higher with Lambda. This suggests that performance-critical code sections will benefit from typical optimisation techniques such as inner functions or local function calls at the expense of more code duplication.

6 Discussion

FaaSification is an emerging technique whose application fields need to be determined. Two interesting and feasible ones are the transformation of (admittedly simple) legacy applications and the continuous local testing of applications under development. The distinct methods include so far both static and dynamic decomposition of modules into functions, but not yet functions into smaller functions to avoid hitting deployment limits in the target services described in this paper. New concepts are needed to manage the resulting tiny microservices, or nanoservices. Current management systems, including AWS Lambda and the related AWS API Gateway, are evidently optimised to handle few higher-value functions instead of massive amounts of smaller functions. The elimination of
duplicated dependency code and the optimal selection of function instance sizes due to their influence on execution performance will be other targets for future research.

Even with the prototypical nature of Lambada, the tool already proves useful in programming education beyond computer science and engineering curricula. Students often struggle with formulating their algorithms. Deploying functions individually in a manual process would introduce a chilling effect and reduce the motivation to focus on the core problems significantly. Automated decomposition and deployment assist to maintain the motivation.

7 Conclusion

Automated code deployment and transparent code offloading to FaaS are interesting new workflows in cloud application software engineering and testing scenarios. This paper has introduced and explained Lambada, a tool to automate this workflow. The tool shifts Python functions and methods along with module-internal code dependencies into hosted function services implementing the AWS Lambda management interface. While the overheads are significant, they are determined mostly by constants whose effect is reduced in more complex function with a runtime of more than a few seconds. This makes the approach feasible for a number of development and testing tasks regularly performed by cloud application engineers.

Repeatability

Lambada is publicly available at [https://gitlab.com/josefspillner/lambada](https://gitlab.com/josefspillner/lambada). The repository contains the Fibonacci functions references in this paper among other examples. To repeat the experiments, a starting point is the invocation of `./lambada -debug -local examples/fib.py` which rewrites the script containing the function locally for inspection and informs about the transformation process. Omitting the flag `-debug` is recommended for measurements. Omitting `-local` furthermore performs the deployment and execution in the Lambda environment assuming the AWS CLI tools are installed, configured and working correctly.

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