Active-Code Replacement in the OODIDA Data Analytics Platform

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Abstract. OODIDA (On-board/Off-board Distributed Data Analytics) is a platform for distributing and executing concurrent data analysis tasks. It targets a fleet of reference vehicles in the automotive industry and has a particular focus on rapid prototyping. Its underlying message-passing infrastructure has been implemented in Erlang/OTP, but the external applications for user interaction and carrying out data analysis tasks use a language-independent JSON interface. These applications are primarily implemented in Python. A data analyst interacting with OODIDA uses a Python library. The bulk of the data analytics tasks are performed by clients (on-board), while a central server performs supplementary tasks (off-board). OODIDA can be automatically packaged and deployed, which necessitates restarting parts of the system, or all of it. This is potentially disruptive. To address this issue, we added the ability to execute user-defined Python modules on both the client and the server, which can be replaced without restarting any part of the system. Modules can even be swapped between iterations of an ongoing assignment. This facilitates use cases such as iterative A/B testing of machine learning algorithms or deploying experimental algorithms on-the-fly. Active-code replacement is a key feature of our system as well as an example of interoperability between a functional and a non-functional programming language.

Keywords: Distributed computing, Concurrent computing, Distributed Data Processing, Erlang

1 Introduction

OODIDA [12] is a modular system for concurrent distributed data analytics, with a particular focus on the automotive domain. It processes telemetry data at its source as opposed to transferring all data over the network and processing it on a central server. Our system facilitates rapid prototyping of data analytics methods in a fleet of reference vehicles. A data analyst interacting with this system uses a Python library that assists in creating and validating assignment specifications. Several domain-specific algorithms and methods of descriptive statistics have been implemented. However, updating the software that is executed on client devices is
time-consuming and disruptive as it necessitates terminating and redeploying the 
client application. Ideally, we would like to update the client without interrupting 
any currently ongoing tasks. As a consequence, we have extended our system 
with the ability to execute custom code, provided by the data analyst, without 
having to redeploy software to client devices. With this extension, users can 
define and execute custom computations both on client devices (on-board) and 
the server (off-board).

In this paper, we describe active-code replacement in OODIDA. We start 
off with relevant background information in Section 2, which includes a brief 
overview of the target system. In Section 3 we cover the implementation of this 
feature, showing how Erlang/OTP and Python interact. We also elaborate on 
the reasoning behind our design considerations, including the deliberate limitations 
we have placed on our modification. Lastly, in Section 4 we describe related work.

Fig. 1: OODIDA overview and details: In (a) user nodes $u$ connect to a central 
cloud application $b$, which connects to clients $c$. The colored nodes are imple-
mented in Erlang/OTP; the other nodes are external Python applications, i.e. 
the user front-end $f$ and the external client application $a$. In (b) the core of 
OODIDA is shown with permanent nodes (red) and temporary handlers (blue). 
Clients $x$, $y$, and $z$ spawn task handlers $x'$, $y'$, and $z'$ that interacts with external 
applications.

2 Background

In this section, we describe relevant background of active-code replacement in the 
OODIDA platform. We start with a brief overview (2.1). This is followed by a 
description of assignment specifications (2.2) and the user front-end application (2.3), 
before we show how our system can be extended with new computational meth-
ods (2.4). This leads to the motivating use case that describes on-the-fly updating 
of the system without taking any of its parts down (2.5).

2.1 OODIDA Overview

OODIDA is a platform for distributed data analytics in the automotive domain, 
targeting a fleet of reference vehicles. A particular focus is the prototypical
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exploration of statistical methods and machine learning algorithms, which are executed on on-boards units (OBUs) that are placed in connected vehicles. It is a distributed system that runs on three kinds of hardware: data analysts use workstations, the server application runs on an internal private cloud, and clients are executed on OBUs. Our system can accommodate multiple users, but for the sake of simplifying the presentation, we mainly focus on a single-user instance.

In Fig. 1a, the context of our system is shown, indicating that a data analyst uses a front-end $f$. In turn, $f$ is connected to a user module $u$ that communicates with the central cloud application $b$ (bridge). The workstation of the data analyst executes both $f$ and $u$. Node $b$ communicates with client nodes $c$ on OBUs. Each client node interacts with an external application $a$. Data analysts use a front-end application $f$ to generate assignment specifications (cf. Sect. 2.2), which are consumed by the user node $u$ and forwarded to the cloud node $b$. On the cloud node, assignments are divided into tasks and forwarded to the chosen subset of clients. On client devices, external applications $a$ perform analytics tasks, the results of which are sent to $b$. On the cloud, optional off-board tasks are performed. Assignments can be executed concurrently.

Building on this more general view, Fig. 1b presents further details of the underlying message-passing infrastructure, which has been implemented in Erlang/OTP. We start with the user node $u$, which is identical to $u$ in Fig. 1a. The user defines an assignment specification with the help of $f$, which forwards it to $u$. In turn, $u$ forwards it via the network to $b$. That node spawns a temporary assignment handler $b'$, which divides the assignment into tasks and distributes them to client devices. In the sample illustration, there are three client nodes $x$, $y$ and $z$. Both the client node and its task handler are executed on an OBU, just like the external application $a$ shown in Fig. 1a. Each client spawns a temporary task handler per received task. For instance, client node $x$ spawns task handler $x'$. Task handlers communicate the task specification to the external application $a$, which performs the requested computational work. Once the results are available, they are picked up by the task handler and forwarded to the originating assignment handler $b'$. Afterwards, the task handler on the client terminates. Once $b'$ has received the results from all involved task handlers, it performs optional off-board computations. It then sends the results to $b$ and terminates. Finally, $b$ sends the assignment results to the user process $u$, which communicates them to $f$. How external applications on the client and cloud interact with the core of our system is shown in Fig. 2.

The specified on-board and off-board computations can be carried out in an arbitrary language as our system uses a language-independent JSON interface. However, we focus on a simplified version of OODIDA that uses Python applications to execute both on-board and off-board tasks.

2.2 The Assignment Specification Format

Listing 1.1 shows an example of an assignment specification as it is defined by a data analyst. If it is successfully validated by the provided Python library, it is turned into a JSON object for further processing. In this example, we perform a
measurement task with all active clients. Below, we go through all fields of the shown code. Active-code replacement uses the existing infrastructure; deploying custom code is encoded as an assignment (cf. Sect. 3.1).

The fields "name" and "description" contain strings of arbitrary length, but the intention is that the former is a short heading. The field "mode" specifies the kind of assignment the user wants to perform. A straightforward one that does not require specifying any additional parameters is "Measurement". The next field is "clients", the entirety of which is selected with the keyword "all". Client nodes $c$ are identified by an ID, which is a unique integer. The user can therefore also address clients with a list of IDs. Lastly, if the provided value is an integer $k$, then the cloud node selects $k$ clients for the assignment, or all available ones, if there are fewer than $k$ active clients. The chosen sensor is "speed". It is possible to specify multiple sensors with a list of strings. The fields "onboard" and "offboard" specify which tasks are performed on the client and on the server, respectively. In our example, "average" triggers averaging the specified measurements onboard, and "collect" the collection of these averages offboard. In which interval signals are read is specified by the keyword "frequency". The provided value has to be a positive integer, representing the unit Hz. Closely tied this keyword is the next one, "samples", which indicates the number of sensor readings to perform. It likewise has to be a positive integer. In our example, we read 1000 values at a frequency of 1 Hz. The key "iterations" takes a positive integer and specifies how often an assignment has to be performed. The results of each iteration are normally retained, although there are use cases where the results of one iteration are used as input for a subsequent one.

2.3 User Front-end Application

OODIDA provides a Python front-end application $f$ for the data analyst for easy creation and validation of assignment specifications. Assignment specifications are JSON objects that follow a particular format, as just detailed. Because their manual creation is error-prone, $f$ automatically verifies the correctness of the provided assignment specification. Checks include completeness and correctness of the provided dictionary keys, type-checking the corresponding dictionary values, and verifying that their range is valid. For instance, the value for the field "frequency" has to be a positive integer and cannot exceed a certain threshold. Separately verifying assignment specifications is necessitated by the rudimentary
type system of Python. In programming languages with a more expressive type system, e.g. Hindley-Milner type inference or Martin-Löf dependent types, some of those checks could be performed by the compiler. If the validation is successful, the configuration dictionary is converted into a JSON object and sent to the user process \( u \), which is also executed on the workstation of the data analyst.

2.4 Extending OODIDA

As OODIDA has been designed for rapid prototyping, there is the frequent need of extending it with new computational methods, both for on-board and off-board processing. In Fig. 2 a simplified representation of the affected nodes is given. In short, to extend the system, the nodes labeled \( cp \) have to be updated. These are the Python applications that perform on-board and off-board computations. They interact with an arbitrary number of assignment handlers (off-board) and task handlers (on-board). In order to update OODIDA with new computational methods, the system has to be modified. For the user, the only visible change is a new keyword and some associated parameters, if needed. Assuming that we update both the on-board and off-board Python application, the following steps are necessary:

- Update user front-end \( f \) to recognize the new off-board and on-board keywords
- Add checks of necessary assignment parameter values to \( f \)
- Add new keyword and associated methods to cloud application \( cp \)
- Add new keyword and associated methods to client application \( cp \)
- Terminate all currently ongoing assignments
- Shut down OODIDA on the cloud and all clients
- Redeploy OODIDA
- Restart OODIDA

Unfortunately, this is a potentially disruptive procedure, not even taking into account potentially long-winded software development processes in large organizations. OODIDA has been designed with rapid prototyping in mind, but although the original system can be very quickly deployed and restarted, it cannot be extended while it is up and running. This was possible with a precursor that was fully implemented in Erlang, which allows so-called hot-code reloading. With Python, this is not easily possible. There are some workarounds to keep the system up-to-date, for instance by automatically redeploying it once a day. As we are targeting a comparatively small fleet of reference vehicles, this is a manageable inconvenience. Yet, users interacting with our system would reap the benefits of a much faster turnaround time if they were able to add computational methods without restarting any of the nodes at all.
2.5 Motivating Use Cases

While the previous implementation of OODDIA works very well for issuing standard assignments, there are some limitations. The biggest one is that adding additional algorithms requires updating the computational node $cp$ on clients or the cloud. This causes potentially ongoing tasks to be terminated and therefore disincentivizes experimentation. Some tasks may have a runtime of hours, after all. Furthermore, there is the problem that it may not even be desired to permanently add an experimental algorithm to the library on the client. This means that experimental execution requires two updates, first to push the code update, and afterwards to restore the state before the update.

The first exemplary use case we consider consists of temporarily adding an algorithm to the external client application. If that algorithm proves useful, it can be added to all clients via an update of the client software. Otherwise, no particular steps have to be taken as the custom piece of code on the client can be easily deleted or replaced by new custom code. A second, and related use case, consists of temporarily adding different algorithms to non-overlapping subsets of client devices. A straightforward example consists of running two variations of an algorithm, with the goal of evaluating them. Thus, actionable insights can be generated at a much faster pace than the procedure outlined in Sect. 2.3 allows.

Lastly, there is the issue of extensibility. Python is a mainstream programming language with a rich ecosystem. There are very extensive external libraries available, which are useful for OODIDA, such as the machine learning libraries Keras [4] and scikit-learn [9]. As those are vast projects, it is infeasible to create hooks for an entire library. Yet, it is occasionally useful to call a function of those libraries, in which case the data scientist can define a custom function that does nothing more than loading the external library and calling that function. Consequently, active-code replacement provides an easy way of quickly accessing the functionality of third-party libraries. This is a much more attractive proposition than extending and redeploying the entire system.

3 Solution

In this section we describe our engineering solution to the problem of replacing active code in our system. We start with the assignment specification the data analyst produces (3.1). Afterwards, we focus on the underlying mechanisms for getting a custom piece of code from the data analyst to the cloud as well as client devices (3.2). This is followed by discussing implementation details that make it possible to keep devices running while swapping a piece of code (3.3). Afterwards, we discuss deliberate limitations of our solution (3.4) and show how a complex use case can be implemented with active-code replacement (3.5).

3.1 The Assignment Specification

In line with the guiding principle that OODIDA should make it as easy as possible for the data analyst to do their job, active-code replacement has been designed
to minimize intervention. The data analyst only has to carry out two steps. The first is providing a stand-alone Python module with the custom code. It could include imports, which, of course, the user has to ensure to be available on the targeted machines. The only requirement on the code is that it contains a function "custom_code", which takes exactly one argument. This is the function that is called on the cloud or client. If there is a need for additional parameters, they have to be hard-coded. Active-code replacement is executed as an assignment. When updating custom code on the cloud, the required mode is "deploy_offboard"; for custom code on clients it is "deploy_onboard". In the latter case, the field "clients" also has to be set. In either case, a field "filename" that specifies the location of a Python module also has to be provided. It is possible to send different modules to different subsets of clients via subsequent assignments.

The verification process of assignment specifications done by the user front-end application consists of two steps. First, the provided module has to be syntactically correct, which is done by loading it in Python. The second check targets the prescribed function name. That function is called with the expected input format, depending on whether it is called on the client or the cloud. We also verify that the returned values are of the expected type. If any of these assertions fails, the assignment is discarded. Otherwise, the custom Python module is sent to the cloud or to clients, depending on the provided instructions. This step is preceded by producing another assignment specification that, in either case, contains the entries "user_id" and "custom_code". The value of the latter is an encoding of the user-provided Python module. The value of the key "mode" is either "deploy_offboard" or "deploy_onboard". Once custom code has been deployed, it can be referred to in assignments by setting the value of the keys "onboard" or "offboard" to "custom".

3.2 Code Forwarding

Assuming the provided custom code for the client has passed the verification stage, it is turned into a JSON object and ingested by the user module for further processing. Within that JSON object, the user-defined code is represented as an encoded text string. The user module extracts all relevant values from the provided JSON object and forwards it to the cloud process. In turn, this spawns a new assignment handler for this particular assignment. The next step depends on whether custom code for the server or client devices has been provided.

The process of turning an assignment into tasks for client devices does not depend on the provided values and is thus unchanged from the description in the paper on OODIDA [12]. Node b' breaks the assignment specification down into tasks for all clients specified in the assignment. After this is done, task specifications are sent to the designated client processes. There, the client process spawns a task handler for the current task. Its purpose is to monitor task completion, besides alleviating the edge process from that burden and enabling it to await further task specifications. In our case, the task handler sends the task specification in JSON to an external Python application, which turns the given code into a file, thus recreating the Python module the data analyst initially
provided. The name of the resulting file also contains the ID of the user who provided it. After the task handler is done, it notifies the assignment handler and terminates. Similarly, once the assignment handler has received responses from all task handlers, it sends a status message to the cloud node and terminates. The cloud node sends a status message to inform the user that the custom code has been successfully deployed. Deploying custom code to the cloud is similar, the main difference being that $b'$ communicates with the external Python application $cp$ running on the cloud.

### 3.3 Code Replacement

If a custom on-board or off-board computation is triggered by the keyword "custom", Python loads the user-provided module using the function `reload` from the standard library. The user-specified module is located at a predefined path, which is hard-coded as an argument for the reload function. Once loaded, the custom function is applied to the available data in the final aggregation step, which is performed once and at the end of a task. When an assignment using a module with custom code is active, the external applications reload that file with each iteration. This approach may be unexpected, but it leads to greater flexibility. Consider an assignment that runs for an indefinite number of iterations. As the external applications can process tasks concurrently, and code replacement is just another task, the data analyst can, for instance, react to intermediate results by deploying code with modified algorithmic parameters that will be used for an ongoing assignment with multiple iterations as soon as it is available. As custom code is tied to a user ID, there is furthermore no interference due to modifications performed by another user.

### 3.4 A Complex Use Case

The description of active-code replacement so far indicates that the user can execute arbitrary code on the server and clients, as long as the correct inputs and outputs are consumed and produced. What may not be immediately obvious, however, is that we can now even create ad-hoc implementations of the most complex OODIDA use cases, an example of which is federated learning [8]. The key difference of it is that the results of one iteration are used as the input to the next one. The original implementation is mentioned in the paper on OODIDA [12]. In contrast, with active code-reloading, federated learning can be implemented as follows. The client executes custom code that trains a neural network based on local data. Its return value is a flattened list of lists that represents the weights of an artificial neural network. The server executes custom code that averages all incoming weights. Instead of the server directly sending new weights to clients, they are sent to the user instead. In addition, the user initializes the weights of an artificial neural network and hard-codes them in the code that is deployed to the server. For each iteration, the custom server code computes new weights, which are sent to the user. In turn, the user deploys new custom off-board code with the updated weights — after the analyst receives these new global weights,
they are added to the custom off-board code prior to redeployment. All of this can be done automatically as control flows can be defined by the user as Python scripts.

3.5 Limitations

We consider custom modules a temporary solution. Any function that is deemed generally useful should be added to computational nodes \( cp \) in an update. We also want to discourage data analysts from heavily relying on custom functions. Currently, they can each define one custom module for the cloud, and one for the client. It would be straightforward to add the ability to handle multiple custom modules per user. Yet, we do not want multiple custom functions to be part of their regular workflow.

4 Related Work

The engineering challenge described in this paper is an extension of the OODIDA platform [12]. It was originally an Erlang-only system based on \( \texttt{ffl-erl} \), a framework for federated learning [11].

Active-code replacement is a niche topic in applied computing, despite its use in fault-tolerant systems. That it is a niche topic is obvious from the fact that there is no uniform terminology. For instance, the official Erlang documentation calls it code replacement.\(^3\) Among working Erlang programmers, the terms hot-code loading or hot-code swapping are more common. In contrast, the standard textbooks by Cesarini et. al [1,2] refer to it as upgrading processes. In academia, we encounter further names for this concept. In an extensive survey by Seifzadeh et al. [10] the term of choice is dynamic software updating. According to their terminology, our approach is called updating references of all dependants. Giuffrida and Tanenbaum [5,6] call it live update, further classified as changes to code.

In terms of descriptions of systems that perform active-code reloading, Polus by Chen et al. [3] deserves being mentioned. A significant difference is that it replaces larger units of code instead of isolated modules. It also operates in a multi-threading environment instead of the highly concurrent message-passing environment of OODIDA. We also noticed a similarity between our approach and Javelus by Gu et al. [7]. Even though they focus on updating a stand-alone Java application as opposed to a distributed system, their described "lazy update mechanism" likewise only has an effect if a module is indeed used. This mirrors our approach of only loading a custom module when it is needed.

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\(^{3}\) Refer to the section on Code Loading in the official Erlang documentation: \texttt{http://erlang.org/doc/reference_manual/code_loading.html} (Accessed March 4, 2019)
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