Auto-COP: Adaptation Generation in Context-Oriented Programming Using Reinforcement Learning Options

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Abstract

Context: Self-adaptive software systems continuously adapt in response to internal and external changes in their execution environment, captured as contexts. The Context-oriented Programming (COP) paradigm posits a technique for the development of self-adaptive systems, capturing their main characteristics with specialized programming language constructs. In COP, adaptations are specified as independent modules that are composed in and out of the base system as contexts are activated and deactivated in response to sensed circumstances from the surrounding environment. However, the definition of adaptations, their contexts and associated specialized behavior, need to be specified at design time. In complex cyber physical systems this is intractable, if not impossible, due to new unpredicted operating conditions arising. Objective: In this paper, we propose Auto-COP, a new technique to enable generation of adaptations at run time. Auto-COP uses Reinforcement Learning (RL) options to build action sequences, based on the previous instances of the system execution (for example, atomic system actions enacted by human operators). Options are further explored in interaction with the environment, and the most suitable options for each context are used to generate the adaptations, exploiting COP abstractions. Method: To validate Auto-COP, we present two case studies exhibiting different system characteristics and application domains: a driving assistant and a robot delivery system. We present examples of Auto-COP to illustrate the types of circumstances (contexts) requiring adaptation at run time, and the corresponding generated adaptations for each context. Results: We confirm that the generated adaptations exhibit correct system behavior measured by domain-specific performance metrics (e.g., conformance to specified speed limit), while reducing the number of required execution/actuation steps by a factor of two showing that the adaptations are regularly selected by the running system as more appropriate than the execution of atomic actions. Conclusion: Therefore, we demonstrate that Auto-COP is able to increase system adaptivity by enabling run-time generation of new adaptations for conditions detected at run time, while retaining the modularity offered by COP languages, and reducing the upfront specification required by system developers.

Keywords: context-oriented programming, reinforcement learning, macro actions, option learning, self-adaptive systems.

1. Introduction

Self-adaptive systems [1] gather information from the execution environment (both internal and ex-
from other adaptations.

Three main concepts are behind dynamic adaptations in COP: contexts, behavioral variations, and context activations. Contexts are defined as first class entities of the system that capture meaningful situations from the system’s surrounding execution environment. Behavioral variations realize modular partial behavior (e.g., a method) specifications defined in isolation of other components. Context activations take place whenever the situations they represent are sensed in the environment, composing their associated behavioral adaptation into the system. In this manner, the dynamic composition model used in COP reifies the MAPE (Monitor-Analyze-Plan-Execute) loop [3].

COP has been used to model self-adaptive systems in general [4, 5]. Concretely, COP Monitors specified system variables or the surrounding environment in the Context Discovery (internal) module [6]. Monitored variables are used for context activation. Taking into account the values for variables, the Context Manager determines whether to activate or deactivate a context; serving as the Analysis phase of the MAPE. In COP, adaptation Planning is implicit and managed by the language, as adaptations are composed with the system behavior as soon as possible [7]. Adaptation Execution is coupled with the planning, as adaptations are enacted whenever contexts are activated, or upon their use. Finally, note that the Knowledge component is only present implicitly in COP. The knowledge for adaptations is encoded within the aforementioned modules, as the system uses as a precondition the fact that adaptations are appropriate to their context, and the context is sensed from the environment.

COP has proven effective in achieving dynamic adaptations [5, 8–13], although latent problems arise from the definition of adaptations. The behavior of adaptations still needs to be defined beforehand by developers. This is a challenging task, and in many cases not viable, as the execution environment may be unknown.

To address the problem of upfront definition of adaptations, in this paper we propose Auto-COP, a new technique to further system automation by enabling the dynamic generation of required adaptations in COP. Auto-COP uses Reinforcement Learning (RL) options [14] to build action sequences, based on the previous instances of the system execution (for example, actions enacted by system users). An RL option encodes sequences of actions, and is defined by a set of states in which it can be initiated (i.e., contexts in COP terminology), an internal policy (i.e., sequence of actions to take), and a terminating condition (i.e., context deactivation). Through options, Auto-COP identifies sequences of actions (referred to as atomic actions in RL options terminology, the term which we also adopt in this paper) and the environmental conditions in which these take place, extrapolating them to behavioral variations and their associated context, to realize dynamic adaptations as in COP. As a consequence, we generate adaptations from learned options, that can be autonomously executed whenever their context is sensed. Note that action sequences executed for a particular situation (e.g., program state) can differ during execution. By using options, Auto-COP can differentiate between the executed atomic action sequences, and via interactions with the environment learn the option that is currently most appropriate for the system execution.

To illustrate the problem and our approach, we consider the case of a driving assistant system (further discussed in Section 4.1). Vehicles are controlled by five atomic intervention actions: straight, steer right, steer left, speed up, and slow down. The driving process consists of a series of actions, which are frequently repeated in response to certain conditions on the road. For example, in Figure 1, when vehicle v1 encounters v2 driving at a lower speed lower than its own, it performs actions steer left and steer right in order to overtake it. When it encounters the next vehicle, v3, the same actions steer left and steer right are repeated. Such ordered sequences of actions are precisely the kind of behavior that Auto-COP could identify, group, extract, and generate COP-based adaptations to automate behavior as an enhancement to the driving assistant system.

![Figure 1: Driving assistant overtaking scenario](image)

In this example, the base system behavior is to drive straight on the right-lane of the road. To keep appropriate behavior of the system under different situations we must adapt its behavior, executing different behavior for particular situations. Such situations are defined as execution contexts. For example, on the left-hand side of Figure 1 v1 is in a
special situation, with a close proximity to v2. This is defined as a context. Associated to the context, we can define a behavioral adaptation, a specialization of the base behavior, in our case, consisting of the steer left and steer right behavior. The combination of the context and its associated behavioral adaptation constitute an adaptation. Once defined, every time the system senses the context, for example by means of external sensors, it triggers the context activation, which effectively composes the behavior associated with this context with the application. Whenever the context is no longer sensed, it is deactivated, effectively withdrawing the associated behavioral adaptations from the application, and reverting it to its base behavior.

While our motivating example is simple, in complex cyber physical systems such sequences might have dozens or hundreds of steps. For example in Minecraft, a complex game environment which is extensively used for novel RL techniques benchmarking, RL options were successfully used to build action sequences and reduce the number of steps in a trajectory 100-fold, from 10,000 steps to only 100 [15].

The main advantage of Auto-COP is that it allows adaptivity of self-adaptive systems, by enabling run-time generation of new adaptations using RL, while retaining modularity and remaining compatible with existing COP tools and techniques. Using Auto-COP, new behavior that corresponds to newly arisen contexts, not foreseen at design time, do not require software developers to specify and incorporate them into the system. Rather, Auto-COP is the first approach to enable building COP adaptations on-line from actions executed during user interactions or operator interventions at run time. In such a way, the system can learn directly from human users and/or operators, removing the need for manual intervention when the given context arises in the future. In addition, if previously defined or generated adaptations are not suitable to respond to a given context any longer, new ones will be generated and overwrite old unsuitable behavior, without the involvement of developers. While "pure" RL-based techniques have been used extensively in self-adaptive systems to achieve runtime adaptation [16], such approaches are fully offline and still require upfront definition of adaptations [17]. Moreover, existing approaches in the literature are application-specific and lack the modularity and reusability offered by combining RL with COP.

To validate the effectiveness of Auto-COP to generate adaptations at run time that can be integrated with a COP system to drive dynamic adaptations, we apply our technique to two different application domains: a driving assistant and a warehouse robot delivery system. Our evaluation in each case study focuses on two main aspects: verifying that adaptations are automatically generated and used by the system in subsequent executions, as well as that generated adaptations exhibit correct system behavior with respect to system goals. We observe that the system executing the adaptations maintains or improves the performance of the base system executing atomic actions. Furthermore, we observe twofold reduction in required execution/actuation steps to achieve the same tasks. This indicates that the generated options are indeed preferred by the system and that a single step may trigger the execution of multiple actions (a learned sequence) rather than atomic actions. We conclude that Auto-COP is able to increase system adaptivity by enabling run-time generation of new adaptations for conditions detected at run time, while retaining modularity of COP.

In summary, the main contributions of our paper are:

- Auto-COP, a novel approach which utilizes RL options to generate adaptations at run time, based on previous system executions and interaction with the environment. Adaptations are generated as defined in COP, and as such can be integrated into COP-based systems to enable dynamic self-adaptation at run time.
- We detail the steps required to incorporate Auto-COP in a self-adaptive system, providing the specifics of the algorithm and code snippets.
- We apply Auto-COP in two separate application domains and confirm its ability to generate adaptations autonomously, to be dynamically incorporated to, and withdrawn from the system.

The rest of the paper is structured as follows. Section 2 introduces necessary concepts from COP and RL options. Section 3 presents the details of Auto-COP approach, while its evaluation in two case studies is presented in Section 4. In Section 5 we discuss most closely related work in adaptation definitions and code generation using machine learning. Finally, in Section 6 we discuss current shortcomings of Auto-COP and provide directions how to address them in future work.
2. Background

Auto-COP enhances the COP paradigm with a learning technique to generate adaptations from previous observed executions. Before diving into the details of our proposal, this section introduces the main concepts of COP, and RL options, the learning technique used to extend COP. To illustrate both concepts, we use examples from the driving assistant system.

2.1. Context-oriented Programming

The COP paradigm proposes a programmatic technique to dynamically adapt the system’s behavior to the context, in a highly modular and reusable fashion [18]. COP languages provide specialized abstractions fostering the definition of dynamic adaptations as system modules that are independent from each other, and the base system, but yet are highly composable.

COP languages introduce adaptations as the combination of two abstractions, contexts and behavioral variations. Contexts represent situations from the execution environment captured by system variables (i.e., the state) that are monitored internally, or can be sensed by external sensing devices. Whenever specific environment conditions for context objects are satisfied, the contexts are said to be active; otherwise they are inactive. Each context is associated with a set of behavioral variations specifying adaptations to the normal behavior specified by the base system. As contexts become active, their associated behavioral variations are made available in the system—that is, this will be the observed system behavior. Internally, upon context activation, its associated behavioral variations are composed with the system at run time. Context deactivation withdraws all behavioral variations associated with the context from the system at run time. In both cases, the system behavior is effectively adapted.

We use Context Traits\(^1\) [19], a COP extension of ECMAScript, as the implementation language for our proposed approach. However, note that this work is not specific to this language, and is applicable to COP in general. To make explicit the concepts introduced by COP, in the following we show the main COP constructs and their interplay using Context Traits. Constructs defined in other COP languages are conceptually similar, although syntactic differences may exist [20, 21].

Programmatically, contexts are first-class system entities (i.e., objects) that abstract semantically meaningful situations gathered from the surrounding environment (or internal state) of the system, using sensors and monitors. For example, in our driving assistant, a closeProximity context is defined to represent the situation in which a vehicle is in close proximity in front (e.g., \(v_2\) in Figure 1), as shown in Snippet 1.

```javascript
closeProximity = new cop.Context(
  name: "vehicle in close proximity"
)
```

Snippet 1: Static definition of a context object

The context defined in Snippet 1 is abstracted from the information gathered from the environment variables (sensors). In our example, the closeProximity context is associated with the readings from the proximity sensor. Snippet 2 shows the conditions, over the system state, in which the context should be active.

```javascript
if(proximitySensor.receive() < 300)
  closeProximity.activate()
else
  closeProximity.deactivate()
```

Snippet 2: Context activation conditions

Whenever a sensed variable satisfies a specified condition, the context defined by the variable is activated using the COP activate() construct. If the condition is no longer satisfied, the context is deactivated using the COP deactivate() construct. As contexts are activated, their associated behavioral variations (explained next) are composed with the running system, enabling the behavior they define, and overwriting/extending the behavior previously defined. As contexts are deactivated, the system is recomposed not to take into account the behavioral variations associated with the context.

Behavioral variations are first-class system modules, providing fine-grained partial behavior definitions of system entities (e.g., new states, or behavior specializations). For example, the specialized behavior to manage proximity to a vehicle can be defined as in Snippet 3, effectively adapting the base drive behavior (continue straight()) defined for the vehicle, with new actions to execute instead

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\(^1\)Available at https://www.npmjs.com/package/context-traits
(i.e., \texttt{steerLeft()} and \texttt{steerRight()}). As explained before, the vehicle should steer to avoid the slow vehicle in front. The sensed \texttt{closeProximity} context is associated with its behavioral variations by means of the \texttt{adapt} construct, as shown by Line 7 of Snippet 3.

Putting contexts, behavioral variations, and context activation together, we adapt the behavior of a program at run time by the dynamic recomposition of the system behavior upon context activations.

```
1 closeProximityBehavior = Trait({
2   drive: function () {
3     steerLeft()
4     steerRight()
5   }
6 })
7 closeProximity.adapt(vehicle, closeProximityBehavior)
```

Snippet 3: Statically defined behavioral adaptation to avoid slow vehicles in front

Behavioral variations define sequences of actions (i.e., functions) to execute whenever a particular context is sensed. In Auto-COP, we automate adaptation definition given a context and a sequence of actions, similar to the proposal of RL option learning, which we present next.

2.2. Reinforcement Learning Options

Temporally extended actions (e.g., macro actions) are used in Artificial Intelligence applications to ensure robustness and build in prior knowledge into applications, from early work on building and executing robot plans [22] to recent applications in deep learning [23]. In particular, in RL, macro-actions are used to speed up learning, or to minimize the periods of suboptimal performance during exploratory interaction with the environment. We consider RL-based macro-action techniques, called options [24], to be suitable for learning and integrating sequences of actions into COP-based adaptive systems. Adaptations in COP respond to changes in the context, akin to the way actions in RL are learned and taken in response to observed environment conditions.

RL is a learning technique that learns optimal actions for specific environment conditions by trial-and-error based on interactions with the environment. At each timestep, an RL agent perceives the environment and maps it to a state $s_i$ from its state space $S$. It then selects an action $a_i$ from its action set $A$ and executes it. The agent receives a reward $r_i$ from the environment when it transitions to the next state, based on which it updates the suitability of taking the action $a_i$ in state $s_i$. The agent’s goal is to learn a policy (i.e., the most suitable action for each of its states) to maximize the long-term cumulative reward. The learning rate $\alpha$ determines to what extent new experience overwrites previously learned ones, and the discount factor $\gamma$ determines how much are the future rewards discounted, in order for agents to prioritize immediate actions, but still be able to plan the best longterm actions.

Early interactions with the environment are focused on environment exploration, i.e., actions are picked randomly and uniformly from actions available in a given state, while later stages, after an agent has had a chance to learn the quality of actions, are focused on exploitation—that is, executing mostly those actions known to lead to the highest long-term rewards. An RL option encodes sequences of such actions into temporally-extended actions, and is defined by three components: a policy $\pi$, which is mapping from a set of states $S$ to a set of actions $A$, an initiating condition (or a set of conditions) $I \subseteq S$, and a terminating condition which determines its length. Numerous ways to build options from atomic actions exist, from those that are manual [25] or require domain knowledge [26], to learning options [27], identifying sequences that lead to the fulfillment of subgoals [28], or automatically generating all action combinations but using another layer of learning to narrow down the full set of generated macro-actions to the most useful ones [29]. Options can also be learned from generated behavior histories, by extracting the most commonly used sequences of atomic actions [30]. Option learning in Auto-COP is most closely related to the techniques used in subgoal fulfillment [28], and behavior histories [30].

3. Auto-COP Design

This section presents the design of Auto-COP, our approach for the automated generation of adaptations for self-adaptive systems. We first present the high-level functionality of Auto-COP, and then describe its two main steps: (1) learning action sequences using RL options, and (2) automating the generation of COP-based adaptations using the learned options.
3.1. Adaptation Generation in Auto-COP

In COP, behavioral variations are predefined by developers, explicitly specifying: the adaptation behavior, the base objects affected by the adaptation, the context in which the adaptation takes place, and the conditions for the selection and scoping of such context. However, this information may not be available or known by developers beforehand. This restricts the adaptivity of the system to the known and specified behavior. Furthermore, it is difficult to know whether the predefined adaptations are indeed the most appropriate behavior for the situation in the current environment, as the environment can evolve during the execution.

To address these problems, Auto-COP enables the dynamic generation of adaptations based on previous system executions, and interaction with the environment.

The overall process of automated adaptation generation using Auto-COP is shown in Figure 2. Software systems execute sequences of actions, generating an execution trace of actions. The source of these actions may be predefined behavior, user intervention (which correspond to atomic actions - in blue), or generated by other processes (which correspond to adaptations - in green). The trace of executed actions is used as input for the RL Option learner, which learns the most suitable action sequences for specific environment conditions. These sequences are then used as input of the Adaptation generator, which packages them into reusable COP adaptations, by defining a context object from the system state, and the behavior variations associated with such context from the learned options.

3.2. Learning Options

The process to learn options continuously executes throughout the system’s lifetime. The process consists of generating adaptations from the best suitable options extracted from the system’s execution trace of actions (both atomic actions, and learned options). This process is described using the pseudo code in Snippet 4. To learn options, we observe the set of environment states $S$ (i.e., contexts) accessible by the system (e.g., monitored variables), and the set of (atomic) actions $A$ that can execute for each state (i.e., functions). The Option learner module learns a set of options $O$, which contains a map of all states $s_i \in S$, associated to a set of actions sequences, defined as options $O_i$, available for execution in that state. All option sets $O_i$ are initially empty, as options are learned during the execution.

During the early execution steps, only atomic actions (i.e., predefined or human-enacted) are executed as the system has no custom adaptations built from options yet. The execution of each action is logged in the execution trace, together with the state (i.e., values of known variables) in which it executed (Execution Trace to the right of Figure 2). For each action, we also log the reward based on the effects of that action on the current state. This reward, $r(s_i, a_i)$, can have multiple sources. For example, if the underlying actions are learned using a learning-based system, the reward corresponds to the reward obtained from the environment. If actions are enacted by a human, a fixed positive reward can be associated with each action under the assumption that such interventions are performed by qualified system operators. Finally, a constant reward (e.g., 1) can be given each time a state-action pair is encountered, under the assumption that the actions more frequently executed are those that are more suitable.

Our algorithm first processes the execution trace in the RL Option learner module to populate the options sets $O_i$ in small batches, every batchSize number of steps. We opt for batch processing, as processing after every execution step can be costly, but have a negligible effect on the options generated. The details of the process correspond to the Lines 8-22 of Snippet 4 (OPTION EXTRACTION).

The outcome of this process is $O$, the map of all states identified in the execution trace, each associated to a set of option sequences ranging in length from 1 (i.e., a single action) to the maximum option length $n$. The maximum option length can be either specified externally, calculated experimentally taking into account the frequency and usefulness of recorded sequences, or set to the maximum number of actions required to reach the sys-
\[ S := \{s_1, \ldots, s_n\} \]
\[ A := \{a_1, \ldots, a_m\} \]
\[ O := \{\{s_1, \emptyset\}, \ldots, \{s_n, \emptyset\}\} \]
\[ \text{lastBatchEnd} := 0 \]

// OPTION EXTRACTION
while (true) {
    AtomicActionLog := write \((s_i, a_i, r(s_i, a_i))\)
    if (timestep \( t \mod \text{batchSize} == 0 \)) {
        // build options from batches in the execution trace (Log)
        for (i=lastBatchEnd; i<\logSize; i++) {
            // read the state from the Log
            loggedState := readLogLine(i, statePosition)
            for (j=0; j<\maxOptionLength && \text{!goalReached}; j++) {
                // read action from the Log
                actionSequence := readLogLine(i+j, actionPosition)
            }
            \(O_i := \{\text{loggedState}, \text{actionSequence}\}\)
            \(O.\text{add}(O_i)\)
        }
        lastBatchEnd := \logSize
    }
}

// ADAPTATION GENERATION
ReinforcementLearning.initialize \((S, O)\)

currentState := senseEnvironment()
// epsilon-greedy option selection
if (contextAdaptationAvailable(currentState)) {
    selectedOption := currentState.\text{pickAnOption}(\epsilon)
    currentState.\text{activate}() \// execute the adaptation
    currentState.\text{deactivate}()
    ReinforcementLearning.\text{updateOption}(S, O, r(currentState, selectedOption))
} else { \// no options available, execute atomic action
    atomicAction := currentState.\text{pickAction}()
    execute(atomicAction)
}
newCOPAdaptation := generate(currentState, highestQOption)
O.\text{add}(newCOPAdaptation)

Snipet 4: Auto-COP run-time adaptation loop

Note that each state may contain multiple extracted options, and the sequences in these options may include previously generated options (shown as "adaptation" in the snippet), following our example. However, most of the extracted options will be unsuitable for adaptation, as they may not yield a correct system state. Auto-COP narrows down options, to select a single option as the most appropriate behavior for each state (context), which we use to generate a COP adaptation. We describe this process next.

3.3. Automated Adaptation Generation

The Auto-COP Adaptation generator module takes as input the different options for each explored state and uses an RL process to learn the most appropriate option to execute as an adaptation. The generation process is specified in Lines 25-39 of Snippet 4 (ADAPTATION GENERATION). For each option executed at a given currentState we record the reward for executing the option using standard Q-learning (state, action, reward) updates, aiming to maximize long-term system performance. After sufficient exploration, the options with the highest Q-values (i.e., highest expected long-term rewards) for each state are identified. The reward model for options takes into account the system reward for reaching the final state of the option. We use this model as we are interested in the system to reach its final goal, only those options closing the gap from the current state to the system’s goal state. To illustrate the generated output, Snippet 5 shows a generic example of possible action sequences for the states stateVariablesSet1 and stateVariablesSet2.

Snipet 5: Ordered action sequences extract
goal state are considered as more appropriate. The options with the highest reward are the ones used in the Adaptation generator module, to generate the context and behavioral variation objects.

```javascript
ContextCurrentState = new cop.Context({ name: "currentState" })
BehavioralVariation = Trait({
    option : function () {
        // learned action sequence
        action1();
        ...
        actionn();
    }
});
ContextCurrentState.adapt(BaseSystem, BehavioralVariation);
```

Snippet 6: Adaptation generation stub

The definition of generated contexts is shown in Line 1 of Snippet 6. Each context is given as a name the string literal corresponding to the state in which it must take place. The generation of behavioral variations constitutes the re-definition of the system’s base behavior, by using the sequence of actions of the selected option, as shown in Lines 2-9 of Snippet 6. Finally, we also generate the association of behavioral variations with their respective context; this is done in Line 10 in Snippet 6.

Once adaptations are generated, while the system further executes, whenever the context associated with one of the adaptations is sensed, the system activates the corresponding context, `ContextCurrentState.activate()`. This triggers the composition of the behavioral variation associated with the context with the system to be executed. Once the behavioral variation executes, the context is deactivated, `ContextCurrentState.deactivate()`, and the system reverts to its base behavior executing atomic actions.

This process continuously executes during the lifetime of the system: traces are logged, processed into options in batches, and their suitability explored in interaction with the environment to propagate the most suitable options into COP adaptations. As the system executes, executed options can be taken into account for the generation of new options, effectively composing options within options. Additionally, note that, if and when the environment conditions change, the appropriateness of adaptation may change, new options can receive a better reward than the options used to generate the current adaptations (e.g., adaptations get a negative reward, or different atomic actions will be executed by the system users). Such process enables the continuous generation of adaptations. In this way Auto-COP removes the need for adaptations to be predefined at design time and ensures the system can continuously adapt as conditions change without manual changes to the source code. In the next section we illustrate applications of Auto-COP in two case studies, and evaluate its performance in satisfactorily generating adaptations that meet specified system goals.

4. Validation

This section shows the feasibility of Auto-COP as a means to automate adaptation generation in self-adaptive systems. To validate our approach, we present two different case studies in which we validate our adaptation generation technique by exploring different system characteristics and application domains. The objective of these case studies is to evaluate the correctness of generated behavior (i.e., it does not lead to errors), and is beneficial towards the system goal, measured according to application-specific metrics), and the usefulness of generated adaptations in the system (as opposed to executing only atomic actions).

4.1. Driving Assistant

Our first case study consists of a driving assistant system, with the purpose of assisting drivers while driving in a two lane highway, as briefly introduced in the motivation in the introduction (Section 1). The objective of this case study is to evaluate the correct generation of adaptations from observed behavior (i.e., it does not lead to errors).

The expected system behavior is to drive in the righthand side lane, and only use the left lane to overtake, if the vehicle in front is driving too slowly. The vehicle has three goals: to drive at or under the speed limit, avoid crashing into other vehicles in front of it, and avoid driving in the left lane. We use the vehicle behavior with respect to these goals to measure the system’s performance. The evaluation metrics correspond to the number of times the vehicle crashes, the number of times the vehicle is in the wrong lane, and the number of times the vehicle drives over the speed limit. All three metrics should be minimized.
4.1.1. Environment

For the driving assistant scenario, we developed a small simulation environment in JavaScript.\(^2\)

The system’s environment consists of a two lane road of 500km. The road speed limit is set to 60km/h, with other traffic vehicles appearing with a 10% chance, at least 3 time steps after the last vehicle is left behind. Traffic vehicles drive at a speed of 30km/h (so that they can be overtaken) and always appear on the driving lane (e.g., the righthand lane in the environment). The vehicle’s atomic actions are to speedUp() and slowdown() (each modifying the current speed by ±10km/h from the current speed), going straight() to maintain the current speed, steerLeft() to move from the right lane to the left lane, and steerRight() to move from the left lane to the right lane.

All the experiments were executed locally on a MacOSX system using version v18.8.0 of Node.js.

4.1.2. Execution

To generate a log of atomic actions for our driving assistant to learn from, we develop an RL algorithm that learns the correct driving behavior for the vehicle from the atomic actions. Note that Auto-COP is agnostic with respect to the origin of such actions in the execution trace (e.g., actions could be generated by human interventions, but as manually controlling a vehicle for the duration required for significant evaluation is cumbersome, we automated the atomic action generation using RL). In addition, by using RL to generate atomic actions, the system occasionally executes an erroneous action (when it is exploring), therefore allowing us to illustrate how option generation corrects for those actions by generating adaptations based on their impact on the system execution rather than just merely repeating execution traces.

In the (atomic) action learning process, the state space of the driving assistant is given by the vehicle’s speed, taking discrete values multiple of 10km/h in the interval [0,70], the current driving lane, modeled as 0 for driving on the right lane and 1 for driving on the left lane, and the proximity to the car in front, divided in the discrete interval [1,4], describing the time steps to reach the vehicle in front. A proximity of 4 denotes that there is no vehicle in front, while values 1, 2, and 3 denote there is a vehicle in immediate proximity in front, and a crash is to occur in 1, 2, or 3 time steps into the future if no action is taken. The reward model penalizes crashing (−8), driving in the wrong lane (−5), driving over the speed limit (−6), driving too slowly (−6), and provides a positive reward when driving in the right lane with no car in front (8).

The learning rate \(\alpha\) is set to 0.1, the discount factor \(\gamma\) to 0.6, and action selection is \(\epsilon\)-greedy, with \(\epsilon\) starting at 0.2 in the exploration stage, reducing to 0.001 in the exploitation stage.

We let the training RL system run for 8000 steps, generating an execution trace of 8000 atomic actions. In the execution trace, for each action we record the current system state [speed, lane, vehicle_proximity], the (atomic) action executed, the next state after executing the action, and the reward obtained by executing said action.

After the execution traces are recorded, we execute the OPTION EXTRACTION stage, Lines 8-22 of Snippet 4, to build possible options (action sequences). Based on the execution trace, in this step we generated a total of 26 options for execution in 13 different states. Only one option is selected for each state to generate the appropriate adaptation. Note that there are 72 total states in the environment, but some of the states do not have any associated options in consequence of two reasons: some states are not experienced during exploration (i.e., do not appear in the execution trace), and we are only interested in generating options for the states in which adaptations are required (i.e., only when system’s goals are not met). If the vehicle is driving at the correct speed limit (state value 60km/h), in the correct lane (state value 0), and there is no vehicle in front (state value 4), then no adaptation is required.

To illustrate this process we focus on the example of the overtaking behavior (not pre-defined as an atomic action) when a traffic vehicle appears in front. Table 1 shows all the extracted options for two of such states. Intuitively, overtaking a vehicle in front is done by a maneuver sequence \{steerLeft (), steerRight ()\} of atomic actions. Therefore, the desired adaptation in the state [50,0,1] is option number 1 in the table, as it overtakes the vehicle in front, while also speeding up to the target speed of 60km/h, to end up in the goal state [60,0,4]. Similarly, in the state [60,0,1] the desired behavior is option 1, to overtake a vehicle without any additional actions. Indeed, the frequency of the execu-

\(^2\)Available at: https://github.com/FLAGlab/DrivingAssistant
Table 1: State space for the learned options and the corresponding generated adaptations in the driving assistant case study

| State | No. | Action sequence | Executions |
|-------|-----|-----------------|------------|
| 50 0 1 | 1 | {steerLeft(), speedUp(), steerRight()} | 29 |
| 50 0 1 | 2 | {steerLeft(), speedUp(), steerRight(), steerLeft(), steerRight()} | 3 |
| 60 0 1 | 1 | {steerLeft(), steerRight()} | 656 |
| 60 0 1 | 2 | {steerLeft(), steerLeft(), steerRight()} | 1 |
| 60 0 1 | 3 | {slowDown(), speedUp(), speedUp(), speedUp(), straight(), speedUp(), speedUp(), speedUp()} | 1 |
| 60 0 1 | 4 | {steerLeft(), straight(), steerRight(), steerLeft(), steerRight()} | 1 |

ition of these actions in the original trace file shows these to be the most executed options for these states. However, the table also shows additional options generated for such states. These options were executed a single time during exploration. While we cannot match these traces to an exact situation during the execution, we speculate that option 2 in state [50,0,1] and option 4 in state [60,0,1] are a result of the vehicle encountering a traffic vehicle in its lane immediately after overtaking a first vehicle, resulting in having to repeat the {steerLeft(), steerRight()} maneuver one more time. For option 3 in the state [60,0,1] we speculate that the first incorrect action in the sequence (slowDown()) resulted in the crash of the vehicle, consequently yielding a speed of 0, from which the vehicle had to execute speedUp() 6 times to reach the target state [60,0,4]. The process of adaptation generation should, however, be able to identify these sequences as not suitable, and learn to extract option 1 into a COP adaptation, for each of our example states.

The list of extracted options, states and their associated action sequences, serves as the input to the next stage of the learning process, where we explore options further using RL to identify which option is the most suitable for the system. To do this, we execute the ADAPTATION GENERATION stage, Lines 25-39 of Snippet 4. To generate adaptations we use the same state space, rewards, and learning parameters as specified for the RL process above. However, in this case, we enable the use of all available options for each state, together with the 5 atomic actions. The best option (i.e., the option with the highest reward) is selected to generate a COP adaptation for the given state. We evaluate and present the performance of the system in the exploitation stage, comparing the performance of just using the atomic actions and using the Auto-COP combinations of atomic actions and generated adaptations.

Figure 3 shows the effectiveness of the generated adaptations as measured by the performance with respect to the three system goals, comparing the atomic actions implementation and the Auto-COP generated adaptations. First we compare the decision points between the two systems, running each of them for 8000 execution steps. In accordance with the use of options, the less decision points the agent takes, the faster is going to be its executions. In our case, since we are executing for 8000 decision points in both scenarios, the efficiency of the agent is given by the amount of atomic actions it executes in those 8000 decision points. The more atomic actions executed, the more adaptations are used by the agent, showing their appropriateness. Figure 3a shows the amount of actions executed by the vehicle when using the generated adaptations vs. using only atomic actions. We actuate a total of 1992 adaptations for the 8000 execution steps (i.e., decision points), resulting in a total of 15516 executed actions vs the 8000 atomic actions (as only a single atomic action can be executed per decision point in a time-step). Therefore, we confirm that the use of options generates suitable sequences of actions, and that the system learns to use those as adaptations to successfully enhance the system behavior, almost doubling the efficiency of system execution, or halving the number of system interventions required.

Second we compare the correctness of using Auto-COP vs. using atomic actions. Figure 3b shows the correctness of the resulting behavior generated by Auto-COP, as the number of rule violations incurred by the vehicle, the fewer violations,
the more correct is the approach. We observe that there are far less lane violations when using adaptations (4 wrong lanes) vs. using atomic actions (34 wrong lanes). We also observe that the vehicle presents an additional crash event (3 crashes) when compared to the atomic actions execution (2 crashes). This can be explained from two perspectives. First, using adaptations, we effectively execute almost twice as many steps that in the case of atomic actions, encountering more than double the amount of cars in traffic (1497 vs. 692), therefore while the total amount of crashes increases, its percentage decreases by 0.25%. This constitutes and improvement over the base system behavior. Second, upon further inspection of the execution trace, we note that two of the crashes take place during the execution of atomic actions, rather than as a consequence of executing the adaptations (as noted previously, the final behavior of the system implementing adaptations is a combination of atomic actions and adaptations, as not all states have adaptations associated with them). Therefore the amount of crashes when using the generated adaptations is further reduced to 50%. Finally, we observe that the number of speed-limit violations increased with respect to the case using atomic actions, going over the speed limit 8 times, vs. 1 speed-limit violation. However, on balance, we can conclude that the use of generated adaptations is beneficial for the system performance, as the overall number of violations across the three metrics significantly decreases.

The adaptations generated by Auto-COP for the two discussed states \([60,0,1]\) and \([50,0,1]\) are shown in Snippet 7 and Snippet 8. In both cases the behavioral variations generated (BAContext6001 and BAContext5001) correctly match the desired overtake behavior.

```javascript
Context6001 = new cop.Context({ name: "Context6001"})

BAContext6001 = Trait({
  option: function(){
    this.steerLeft();
    this.steerRight();
  }
})

Context6001.adapt(agent, BAContext6001)
```

Snippet 7: Generated adaptation for state \([60,0,1]\]

```javascript
Context5001 = new cop.Context({ name: "Context5001"})

BAContext5001 = Trait({
  option: function(){
    this.steerLeft();
    this.speedUp();
    this.steerRight();
  }
})

Context5001.adapt(agent, BAContext5001)
```

Snippet 8: Generated adaptation for state \([50,0,1]\]

To integrate these adaptations, we use COP in
the driving assistant application effectively adapting the application’s behavior from using atomic actions to using the generated behavioral variations whenever appropriate. Snippet 9 shows the definition of the base driving agent (Lines 1-7), together with the overall driving assistant behavior, in which, for each step, depending on the current state, we choose an action to execute (Lines 10-13). If the current state does not have an associated Auto-COP adaptation, we execute a primitive action. If the state has an associated adaptation to it, then we execute the corresponding behavioral variation in the option function. To execute the adaptation we follow the process for dynamic adaptations used in COP, as explained in Section 2.1. First, we activate the context representing the current state (Line 15). This composes the behavioral variation associated to the context with the system. In our example, for the state \( \langle 60,0,1 \rangle \), the behavioral variation in Snippet 7 is composed with the system. The effect of this composition is that the Agent now has an option function defined. Second, we use the behavioral variation by calling the generated option (Line 16). Finally, the system transitions to a different state as a consequence of the option execution, and the context is deactivated (Line 17).

```java
class Agent {
    speedUp () { ... }
    slowDown () { ... }
    steerRight () { ... }
    steerLeft () { ... }
    straight () { ... }
}

while (true) {
    if (qtable[this.currentState])
        action = qtable[this.currentState]
    else
        action = this.randomAtomicAction()
    if (action >= Agent.actions.length) {
        eval('Context${state}'.activate())
        agent.option()
        eval('Context${state}'.deactivate())
    } else
        eval('agent.${actions[action]}')()
}
```

Snippet 9: Integration of generated adaptations using COP

### 4.2. Warehouse Delivery Robot

The second case study focuses on evaluating the correct generation of adaptations and the usefulness of such adaptations. This case study consists of a robot delivery system for a warehouse. The purpose of the robot is to move packages from their storage space in a warehouse to the collection point at the front desk. The robot’s goal is to pick-up a package ready for delivery and take it to the front desk. While the robot does not know where a package is located, once it picks it up, it must take it to the front desk at a defined goal location as specified by a coordinate pair \((x, y)\). The base system behavior for the robot is to roam the warehouse unaware of the packages or the drop-off point. As requests for a package come in, then the robot should go and fetch them. Fetching each of the products in the warehouse then constitutes a special situation, the robot should adapt its behavior to.

#### 4.2.1. Environment

The system environment is delimited by a \( n \times n \) grid (5 \times 5 in our evaluation). The packages are located at specific positions within the grid, different from the point at the front desk. The robot can move to any of the adjacent positions from its current position \((x, y)\), within the boundaries of the environment. Action `north()` is used to move to cell \((x - 1, y)\), `south()` to move to cell \((x + 1, y)\), `east()` to move to cell \((x, y + 1)\), and `west()` to move to cell \((x, y - 1)\). Additionally, the robot has the `pickup()` and `dropoff()` actions to pick-up and drop-off the package respectively, once it is at the correct location.

#### 4.2.2. Execution

Following the same process as in the driving assistant case study, we define an RL algorithm that learns the correct behavior to pick-up and drop-off packages using atomic actions. The robot’s state space is defined by its \((x, y)\) coordinates (with values in \([0, 4]\)), and a single boolean value denoting whether the robot is available for package pickup. The reward model for the robot gives a positive reward (20) for correctly dropping-off the package and (10) for correctly picking it up, and a negative reward (−10) for executing an incorrect action.

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3This example is inspired by the standard RL benchmark Taxi-v3.
4Available at: [https://github.com/FLAGlab/RobotDelivery](https://github.com/FLAGlab/RobotDelivery)
(pick-up or drop-off at a wrong location, picking-up when there is already a package, or dropping-off without a package), all other actions give a small negative reward ($-1$). The learning rate $\alpha$ is set to 0.1, the discount factor $\gamma$ to 0.6, and action selection is $\epsilon$-greedy, with $\epsilon$ starting at 0.2 in the exploration stage, reducing to 0.001 in the exploitation stage.

Unlike the driving assistant which executes continuously without a terminal state, the warehouse delivery robot is an episodic task—that is, the task ends when the package is delivered to the desired destination. Therefore, the execution is organized into episodes.

To create the log of atomic actions from which we extract the adaptations, we first train an RL agent for 600 episodes (i.e., 600 instances of picking-up and dropping-off a package) to explore the state space and find correct routes. In the execution trace we record the action taken at each step, the current robot’s state $[\text{pos}_x, \text{pos}_y, \text{package}]$, the next state after executing the action, and the reward obtained from the action execution.

After the traces are recorded, we execute the option building stage, Lines 8-22 in Snippet 4, to build possible options. Based on the execution trace, in this step we generated a total of 65 options for execution in 11 states (out of total of 50 states). The next step is to reduce available options to the option with the highest Q-value to generate the adaptation, using the adaptation generation stage (Lines 25-39 in Snippet 4). For this we use the same state space, rewards, and learning parameters as specified for the RL process above, while the action set now consists of both the existing atomic actions and all of the generated options.

We compare the performance of the system using the atomic actions and the Auto-COP generated adaptations, during 600 exploitation episodes (we use the same number of episodes as for the RL-only training stage, for ease of comparison with atomic actions). There are no dropoffs to incorrect locations in either the atomic actions case nor the adaptations case, so the performance of Auto-COP preserves correct behavior with respect to the system goal. As there is only a single goal, and is always met in both cases, we do not show graphs for this case study. Instead, we illustrate the resulting behavior, i.e., the path that the warehouse robot took, while executing atomic actions (left-side of Figure 4) vs. the path executing adaptations (right-side of Figure 4).

In the case of atomic actions, a total of 11 actions execute to achieve the goal from the starting location: 9 steps that move the robot around the grid to correct locations, 1 pickup, and 1 dropoff action. In the case of adaptations, a total of only 5 executions took place: an option consisting of step sequence $\{\text{east, south, east}\}$, 3 atomic actions $\text{east, south, pickup}$ and the final option that took the robot all the way from the pickup location to the delivery location, consisting of sequence $\{\text{south, west, south, dropoff}\}$. The generated COP code for this adaptation is shown in Snippet 10. Therefore, we conclude that Auto-COP was successfully applied in the warehouse delivery robot system, as it identified correct action sequences to package into adaptations, resulting in meeting the goal in each episode, and requiring only 4 execution steps to achieve the goal vs. 11 steps required for atomic actions.

```javascript
Context23false = new cop.Context({
  name: "Context23false"
})
BAContext23false = Trait({
  option: function () {
    this.south();
    this.west();
    this.west();
    this.south();
    this.dropoff();
  }
})
Context23false.adapt(agent, BAContext23false)
```

Snippet 10: Generated adaptation for state $[2,3,\text{false}]$
5. Related Work

This section discusses Auto-COP in the perspective of existing related approaches to define adaptations, applications of RL in adaptive systems, as well as code generation techniques using Machine Learning (ML).

5.1. Adaptation Definition

Different techniques have been proposed for the definition of adaptations in self-adaptive systems. From the programming language perspective, existing approaches are based on COP. As previously mentioned, all existing approaches [20, 21] require the upfront definition of adaptations by developers.

From a modeling and architecture perspective, adaptations follow the MAPE feedback loop, in which it is the developers’ responsibility to model and define all system components to be able to monitor the environment information, analyze it, and process and execute the appropriate behavior from a set of available adaptations. Adaptations are introduced into the system using predefined hook-points in the base application. While the MAPE model is most commonly used for the definition of self-adaptive systems, other models such as feedback control loops, the self-management model, or the autonomic computing reference architecture share the property of requiring the upfront definition of adaptations [31].

Advances in big data technology have led to the use of data streams coming from large cyber physical systems and smart city systems to drive the adaptation of their behavior. High-rate data processing enables the definition of an architecture to adapt application behavior based on big data analysis, as presented by RTX [32]. In RTX, applications knobs are defined to change the system behavior based on the analysis of processed data. Unlike Auto-COP, RTX requires the definition of the conditions of the analyzed data in order to enact changes. This is similar to the definition of adaptations (and their conditions), which we do not require in Auto-COP.

Adaptations are managed and defined in the domain of software variability by means of variability models realized using Software Product Lines (SPLs). Magus [33] uses dynamic SPLs for the adaptation of web service composition in the case one of the service components fails. The Magus approach uses a context state model, that must exist beforehand, containing the functional and non-functional properties of services. This model is then used to modify or adapt the service properties when changes are detected. However, this model can only adapt and react to those functional and non-functional aspects already defined for the web services.

Recently, ML approaches have been explored for the definition of adaptations as a means to overcome manual system modeling, or adjusting the models as they evolve [17], similar to the objective of Auto-COP. Jamshidi et al. [17] present an ML algorithm used to learn optimal configurations for a planning robot. The configurations from which the robot learns are given beforehand, and compared with the robot’s plan (i.e., objective) to find the most appropriate configuration for a given state. The configuration is able to change (through online learning) based on the robot’s state. While the online learning follows a similar process to the one proposed in Auto-COP, the robot actions (i.e., configuration) are predefined, unlike the actions we extract for our adaptations, which are learned from previous interactions with the environment.

5.2. Reinforcement Learning in Adaptive Systems

RL is extensively used in (self-)adaptive systems due to its ability to learn suitable system behavior, requiring only interaction with the environment, without an up-front model of that environment, allowing adaptation of the system as conditions change at runtime. Some of the early RL approaches use in load balancing and resource allocation were presented in a manifesto on RL applications in autonomic computing [34], expanding from there to complex multi-agent scenarios. A recent survey [16] found that over half learning-based complex adaptive systems rely on RL for implementation of adaptive behavior. The applications are varied, ranging from large-scale cyber-physical infrastructure (e.g., transportation [35] and smart grids [36]), service composition [37, 38], internet of things [39], information systems [40], and architectural adaptation [41], to name a few, and cover both classical tabular RL approaches and neural network-based Deep RL approaches. However, unlike in COP adaptations, RL-based adaptive behavior is intertwined with the application code, which could lead to decreased code quality [42], decreased maintainability of the codebase and increased technical debt, similar to ML-based applications in general [43]. By combining adaptivity of RL with modularity and reusability of COP, Auto-COP combines the benefits of the two approaches, main-
taining RL ability to adapt online, while reducing entanglement between core codebase and new adaptations. Auto-COP does not necessarily replace the existing RL-based approaches, but can build on top; underlying atomic actions can be generated using existing RL approaches, whether tabular or deep, following which Auto-COP can, using RL options built from generated actions, package them into adaptations.

5.3. Code Generation Using Machine Learning

Auto-COP utilizes RL to generate COP adaptations at run time and therefore can be classified as an ML-based approach for code generation.

The area of code generation using ML is an emerging field due to recent advancement in deep learning techniques and their increased applicability to different areas. A full review of the wider field of deep learning for software engineering and future research directions is presented by Devanbu et al. [44], while Cruz-Benito et al. [45] provide a review and comparison of deep learning approaches to automated source code generation and auto-completion. Applications of learning in the code generation focus on, for example, predicting a sequence of source code tokens [46], generating code based on natural language code descriptions [47], or generating front end code from hand-drawn wireframes [48]. The only work that utilizes RL in this field focuses on source code summarization to generate code comments [49]. To the best of our knowledge, no approach currently utilizes RL options, nor focuses on generating methods out of sequences of existing behavior, as Auto-COP does.

6. Conclusion and Future Work

This paper presents Auto-COP, a new technique for the automated generation of adaptations for self-adaptive systems realized using COP. Our proposal extends the state-of-the-art in COP with an online adaptation engine based on RL options. Auto-COP enables the system to learn the behavior of the adaptations for specific system states, rather than solely relying on predefined adaptations by developers. The online adaptation engine continuously processes execution traces to extract action sequences from the set of atomic actions executed for every state. Taking the extracted state-action sequences (i.e., options), the system learns the most appropriate option, from a set of available extracted options, with respect to the system goal. Learned options are used to generate behavioral adaptations associated with the context in which they should take place. Generated behavioral variations are used to adapt the base-system behavior, whenever their associated context is sensed in the environment.

Our approach is evaluated using systems from two different application domains. In both experiments, we evaluated the effectiveness of Auto-COP in generating and exploiting generated adaptations. Our experiments show that for both systems, first, the most appropriate learned options generated adaptations from previous execution, and second, adaptations are effective in contributing to meet the system goal, whenever their context is activated.

One of advantages of Auto-COP is that it enables learning of adaptations at run time, while retaining the modularity aspects offered by COP. Additionally, Auto-COP is fully compatible with existing COP tools and techniques. Future work should address the integration with such techniques, to enable a more robust context-adaptation approach. For example, conflict between adaptations can occur if multiple contexts are sensed simultaneously, requiring execution of multiple adaptations. Such conflicting interactions can be resolved using a W-learning technique [50], which determines the adaptation with a higher priority, to execute at that particular system state. Similar techniques could be integrated with Auto-COP to compose adaptations whenever multiple adaptations are sensed simultaneously [51].

As generated adaptations become more complex and consist of longer sequences, the possibility of environment changes mid-adaptation increases. In this situation, long sequences of actions being executed without intermediate system state checking would result in inappropriate or even dangerous actions being executed, if adaptations are always executed to completion once triggered. Monitoring for environment changes continuously during adaptation execution and enabling adaptation interruptions is required to guarantee safe system performance. Integration with human-in-the-loop systems should also be investigated, to enable users or operators to override adaptations by means of manual execution of atomic actions when interrupting an adaptation. Such intervention/override can be taken into account in the option learning process as a negative feedback, which will lead to updating
the adaptation based on atomic actions enacted by the human. This should also be done in conjunction with more fine-grained approaches to integrating RL and human feedback (RLHF approaches); currently human actions are "taken for granted", i.e., it is assumed that skilled human operator actions are correct. In reality, those actions can sometimes be inconsistent or even wrong, so integration of Auto-COP with RL-based techniques which are robust to this inconsistency, such as policy shaping [52], can be investigated.

The applicability of this work to other areas of adaptive systems should also be investigated. For example, Self-healing systems [53] provide the capability for systems to diagnose and recover from errors. These approaches use diagnosis components (e.g., root cause analysis [54]) to identify the cause of failures, and the access points (locations) in which a sequence of recovery actions can be used to assure the continuity of the system. The overall functioning of self-healing systems maps to our proposed approach to generate adaptations, understanding adaptations as recovery actions and contexts as the root cause of the failure. Given this mapping, we could learn recovery actions as they take place, and then automate them so that future occurrences of the failure would not require any intervention.

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