Combining Model Learning and Data Analysis to Generate Models of Component-based Systems*

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Abstract. Finding bugs in systems without model is well-known to be challenging and costly. But, most of today's developers think that writing models is also a hard and error-prone task. In this context, this paper addresses the problem of learning a model, from a component-based system, which captures and separates the behaviours of components and encodes their synchronisations. We present a passive model learning method called COnfECt to infer such models from execution traces in which no information is provided to identify components. We describe the two main steps of COnfECt in this paper and show some preliminary experimentations on real systems.

Keywords: Model learning; Passive learning; Reverse engineering; Component-based systems.

1 Introduction

Software testing aims at assessing the quality of the features offered by a system in terms of conformance, security, performance, etc., to discover and correct its defects. Nowadays, testing is essentially performed by means of test cases written by hand, which is often a long, difficult and error-prone task. To make this task easier, model learning approaches have proven to be valuable for recovering models that can be exploited by many software engineering stages, e.g. testing.

Although the generation of behavioural models has been greatly studied, little attention has been given to the learning of models from component-based systems. Yet, most of the systems being currently developed are made up of reusable features or communicating components that interact together. These observations motivate this work, which adresses the challenge of how to learn a model from its traces, in such a way that the model captures the behaviour of every component of the System Under Learning (*SUL*) and their synchronisations.

For this purpose, we designed the method COnfECt (COrrelate Extract Compose) for learning models of component-based systems. Its main originality is that it does not require any preliminary identification information about components. COnfECt learns a system of LTSs (Labelled Transition Systems) from

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traces (passive learning), which captures the behaviours of every component by a LTS and shows how they are synchronised together. COnfECt is composed of two main steps called *Trace Analysis & Extraction* and *LTS synchronisation* which are going to be developped in this paper.

Paper organisation: Section 2 introduces the two steps of the COnfECt approach. The next section summarises the results of a preliminary evaluation on an IOT (Internet Of Things) device. Finally we conclude in Section 4.

2 The COnfECt Approach

Beforehand, we recall that the LTS model, we use in this paper, is defined in terms of states and transitions labelled by actions, taken from a general action set $\mathcal{L}$, which expresses what happens (a more complete definition can be found in [2]). We also define special actions of the form $call\_C_i$ and $return\_C_i$ to model component calls with C_i referring to a LTS. Actions of the form $call\_C_i$ and $return\_C_i$ synchronise pairs of LTSs as described in[1]. The execution of C_i starts with the label $call\_C_i$ and ends when the transition $return\_C_i$ is fired.

2.1 Overview of COnfECt

The COnfECt method aims to infer a system of LTSs SC from the traces of SUL, in such a way that SC captures the behaviours of the SUL components and their synchronisations. COnfECt initially requires the set of traces of SUL, denoted $Traces(SUL)$, to analyse the system behaviours and identify components. We suppose that each component can be identified by its behaviour, materialised by action sequences. And the more traces, the more correct the component detection will be. SUL can be indeterministic, uncontrollable or can have cycles among its internal states. However, we assume SUL and $Traces(SUL)$ obey certain restrictions. We consider that SUL has components whose observable behaviours are not carried out in parallel. One component is executed at a time from its initial state to one of its final states. Furthermore, we consider that traces are collected in a synchronous manner (by means of synchronous communications) to avoid the interleaving of actions. Traces can be collected by means of monitoring tools or extracted from log files. We assume that $Traces(SUL)$ does not include actions expressing the calls of components.

Furthermore, although this task is costly and important, we do not focus this work on the trace formatting, hence, we assume having a mapper, which is a tool often required in model learning to transform raw execution traces into higher level representations.

COnfECt has two main successive steps illustrated in Figure 1. The first step, called *Trace Analysis & Extraction* tries to detect components in $Traces(SUL)$, which is partitioned into a set of trace sets called $STraces$. Each trace set of $STraces$ captures some behaviours of one component. The second step, called *LTS Synchronisation*, takes the set $STraces$ and starts with the generation of one LTS for each trace set of $STraces$. This step also proposes different synchronisation strategies to generate a system of LTSs SC, before merging equivalent states with kTail.

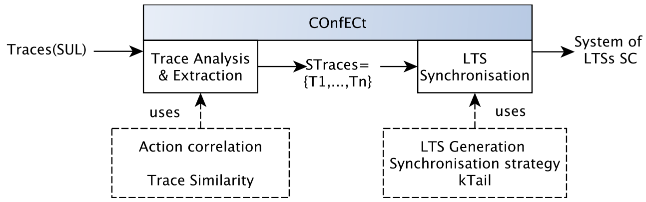


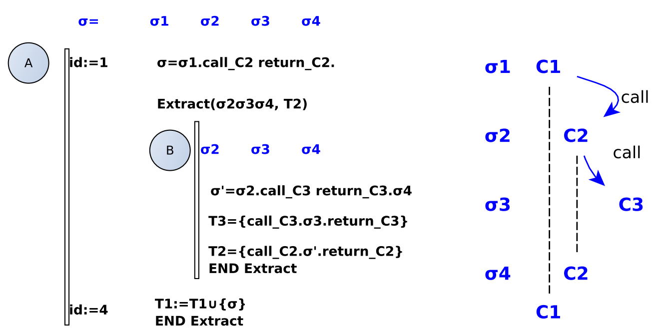
Fig. 1: The COnfECt approach overview

2.2 Trace Analysis & Extraction

The aim of this step is to identify the different components in the traces of $Traces(SUL)$. The algorithm, which is given in [2] is divided into three procedures. The first one, *Inspect* analyses the traces and segments them in sub-sequences. We define a Correlation Coefficient to evaluate the correlation of successive actions in $Traces(SUL)$, i.e. the degree to which successive actions are associated with regard to $Traces(SUL)$. We define the Correlation coefficient between two actions by means of a utility function, which involves a weighting process for representing user priorities and preferences. We have chosen the technique *Simple Additive Weighting* (SAW) [3], which allows the interpretation of these preferences with weights. This factor must take a value between 0 and 1, and needs to be appraised, depending of the context.

From this Correlation coefficient, we define a relation to express the notion of strong correlation. We say that strong-corr(σ_1) holds when σ_1 has successive actions that strongly correlate. Besides, we compare two sequences with the relation σ_1 *mismatch* σ_2, which holds when the last event of σ_1 does not correlate strongly with the first one of σ_2.

The second procedure *Extract* whose algorithm is also given in [2] creates recursively different sequences to express component calls. It takes every trace σ, transforms it and stores the new trace into a set T_j, by the means of the coefficient correlation.



(a) Procedure Extract steps (b) Component call

Fig. 2: Sequence extraction example

Example 1. Let us illustrate the procedure *Extract* with the example of Figure 2a. The procedure takes as input a trace initially segmented into 4 sub-sequences by the correlation coefficient. A) We start at σ_1 and suppose that no other subsequence is strongly correlated with σ_1 . The sequence $\sigma_2\sigma_3\sigma_4$ is hence extracted and replaced by the actions $call\_C2$ $return\_C2$, which model the call of a component $C2$. The procedure is recursively called with Extract($\sigma' = \sigma_2\sigma_3\sigma_4, T_2$). B) We now suppose $\sigma_2\sigma_4$ strongly correlate, thus σ_3 is extracted and the sequence σ' becomes $\sigma' = \sigma_2.call\_C3\ return\_C3.\sigma_4$. The extracted sequence σ_3 cannot be segmented. It is surrounded with the actions $call\_C3$ and $return\_C3$ to prepare the LTS synchronisation and to express that C3 is called by another component. The resulting sequence is added to the set T_3. As σ' is completely covered, σ' is surrounded with the actions $call\_C2$ and $return\_C2$ and added to the new trace set T_2. At the end of this process, we have recovered the hierarchical component call depicted in Figure 2b and we get three trace sets.

The set T_1, which holds the modified traces of the initial traces set $Traces(SUL)$, may include traces resulting from several components. We call the third procedure *Separate* for trying to partition T1, to build the set $STraces$ such that a trace set T of $STraces$ is produced by one component. For that, we evaluate the trace similarity with regard to the actions shared between pairs of traces. Among the different available coefficients, we chose the Overlap coefficient because the action sets used by two traces may have different sizes. Then a clustering technique is used to get the equivalence classes. The procedure Separate is implemented with a Similarity threshold here.

2.3 LTS Synchronisation

The previous step of COnfECt has segmented, extracted and modified the traces of $Traces(SUL)$ in such a way that each traces set contains the behaviour of only one component. We generate a LTS from every traces set, where each trace represent a path of a tree-like LTS. These LTSs include actions of the form $call\_C_i$ and $return\_C_i$. These actions were added in the previous step to prepare the synchronisation of components with LTSs. We proposes different synchronisation strategies, which provide systems of LTSs with different levels of generalisation. The strict synchronisation limits over-generalisation, and used only kTail to merge equivalent states. The weak synchronisation aims at reducing the number of models and allows repetitive components calls, its uses a LTS similary coefficient to merge models by means of a clustering technique. The strong synchronisation generate callable-complete LTSs, i.e., the LTS can call any other LTS of the system from any states.

Example 2. Let us illustrate this step with the set $STraces$ of Figure 3. The traces $T1$ to $T4$ are obtained from the step *Trace Analysis & Extraction* on a trace collected from a real smart thermostat device at the HTTP level. This trace, composed of 16 actions, was formatted to keep the Urls and some data, e.g., the temperature.

We choose to apply the Weak synchronization strategy. A similarity matrix is computed by means of the LTS Similarity coefficient. Figure 4a shows the matrix obtained with the four LTSs of our example. We can observe that two

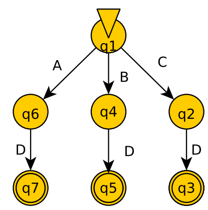
```
STraces = {
T1 {/devices call_C2 return_C2 Response(status:=200,data:=[1]) call_C3 return_C3 /devices
   Response(status:=200,data:=[1]) /hardware Response(status:=200,data:=[2]) /config call_C4
   return\_C4 Response(status:=200,data:=[2]) /tools Response(status:=200,data:=[3])}
T2 {call_C2 /json.htm(idx:=115,svalue:=15.00)=A Response(status:=200)=D return_C2}
T3 {call_C3 /json.htm(idx:=115,svalue:=16.00)=B Response(status:=200)=D return_C3}
T4 {call_C4 /json.htm(idx:=0,switchcmd:=On)=C Response(status:=200)=D return_C4} }
```

Fig. 3: Example of formatted trace segmented into 4 trace sets.

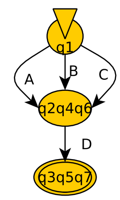
classes of similar LTSs emerge in this matrix: (C_1) and (C_2, C_3, C_4). A clustering technique is used to generate these classes. The LTSs of each cluster are then joined by means of a disjoint union.

	C_1	C_2	C_3	C_4
C_1	1	0,38	0,38	0,38
C_2	0,38	1	1	0,8
C_3	0,38	1	1	0,8
C_4	0,38	0,8	0,8	1

(a) LTS Similarity matrix



(b) LTS C_2_3_4 modelling the sensors



(c) Reduced LTS C_2_3_4

Fig. 4: LTS results

From the trace sets of Figure 3, we obtain the two LTS clusters: (C_1) and (C_2,C_3,C_4), the first one expressing the behaviour of the Web interface, and the other one, the component that sends data. Figure 4b depicts the LTS C_{234} derived from the second cluster. The LTS C_{234} holds two equivalent state classes $(q2, q4, q6)$ and $(q3, q5, q7)$. kTail merges them and returns the LTS of Figure 4c.

3 Preliminary Evaluation

We have implemented COnfECt in a prototype tool on which we conducted several experiments. We initially collected traces from an IOT device, a smart connected thermostat. It integrates 3 components providing HTTP traces. Several experiences have been performed, only five of them are provided in Table 1 and 2 : exp 1 and 2, traces of only one component is recovered, exp 3 and 4, traces of 2 components, and the last one with all the components.

Firstly, we evaluated the capability of COnfECt to recover the correct number of components, and then we compared the number of states and transitions with kTail. The tool, the trace sets and results are available here [1]. In Table 1, for exp. 1 to 5, the number of LTSs is equal to the number of real components with the Weak and Strong strategies, but not with the Strict strategy. This strategy segments traces, which are lifted to the level of LTS, but these are not merged.

Table 2 gives the number of states and transitions of all the LTSs generated by COnfECt in Exp. 1 to 5. We also provide the number of states and transitions of these LTSs after removing the transitions labelled by the synchronisation actions in the last three columns. For comparison purposes, we applied kTail

[1] https://github.com/Elblot/COnfECt

Exp	# real Components	Strict	Weak	Strong
Exp. 1	1	10	1	1
Exp. 2	1	1	1	1
Exp. 3	2	85	2	2
Exp. 4	2	67	2	2
Exp. 5	3	173	3	3

Table 1: Number of components detected by COnfECt.

Exp.	kTail		Strict		Weak		Strong		Strict+hide		Weak+hide		Strong+hide	
	#states	#trans	#states	#trans	#states	#trans	#states	#trans	#states	#trans	#states	#trans	#states	#trans
Exp 1	40	66	152	169	46	78	60	150	120	137	39	70	36	67
Exp 2	6	8	6	8	6	8	6	8	6	8	6	8	6	8
Exp 3	60	115	731	691	104	188	72	183	399	359	71	124	36	85
Exp 4	22	47	496	470	41	81	25	57	236	210	24	55	10	23
Exp 5	85	175	1307	1185	158	286	82	197	627	505	96	169	36	87

Table 2: Size of the LTSs obtained with kTail and the three strategies of COnfECt. The label "hide" refers to the removal of the LTS transitions labelled by synchronisation actions.

on the same trace sets. As expected, we obtain bigger LTSs with COnfECt than the ones achieved by kTail (excepted with Exp. 2 since there is no trace segmentation). This result comes from the functioning of our method since the LTSs are completed with transitions labelled by synchronisation actions.

The transitions labelled by synchronisation actions help interpret the components combination and are required to compose LTSs, but are not relevant if one want to focus on the component behaviours only. If we remove them, the models achieved by COnfECt become more concise than those obtained with kTail.

4 Conclusion

We have introduced COnfECt, a passive model learning method that generates systems of LTSs from execution traces. A system of LTSs captures the behaviours of components and their synchronisations. COnfECt detects component behaviours by analysing traces with a Correlation coefficient and Similarity coefficients. It proposes different LTS synchronisation strategies, which help manage the model generalisation. With this hierarchic component organisation, we believe it offers better readability and comprehensibility than classical learned models, and consequently can be easily used for testing. In future work, we plan to perform more evaluations of COnfECt on several kinds of systems. We also plan to use the models for security testing.

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