Testing Service Oriented Architectures Using Stateful Service Virtualization Via Machine Learning

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Motivation

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As a result of such architectures, today's enterprise software systems have higher number of interconnected services, interdependent teams and heterogeneous technologies.

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- can simulate performance and data characteristics of the real component.
- is useful for *test data management*.

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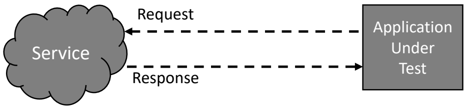

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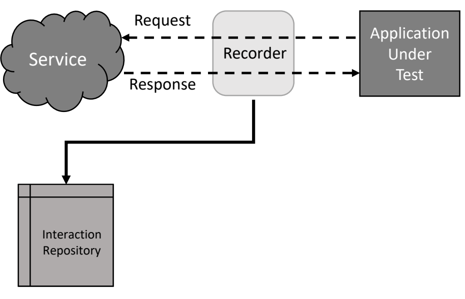

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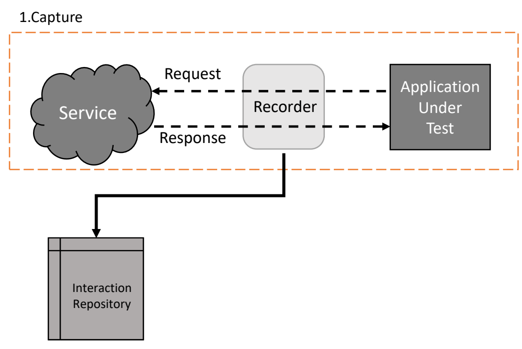

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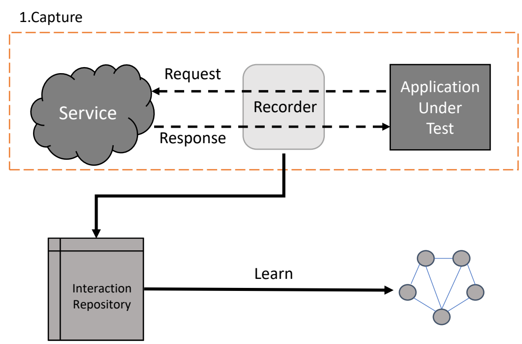

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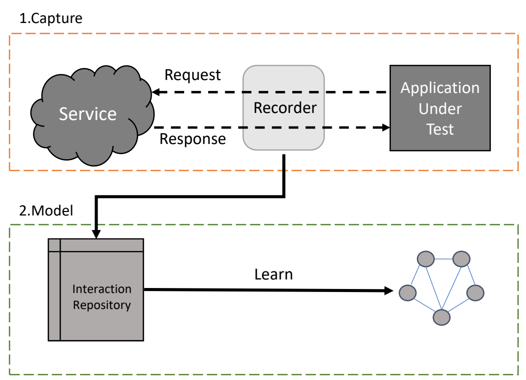

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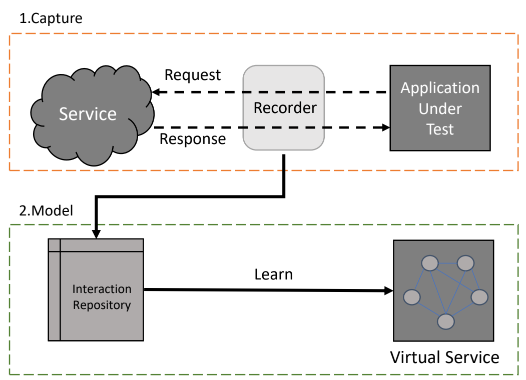

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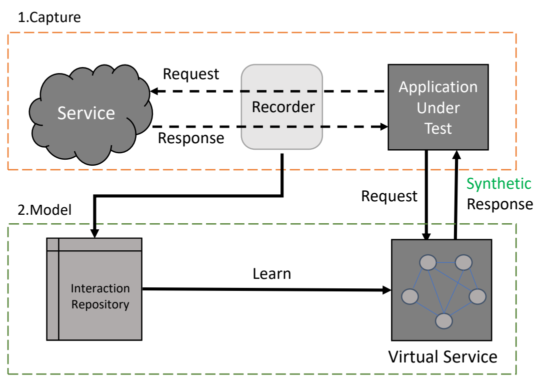

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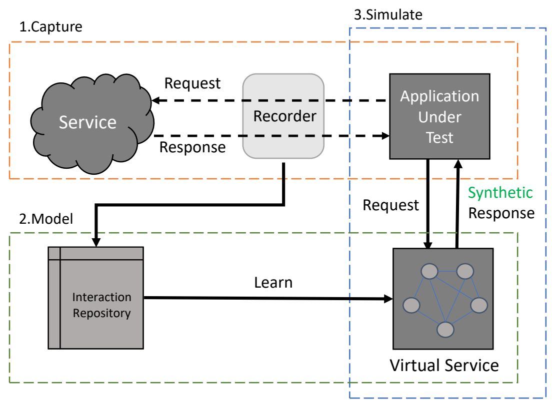

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Another example can be calender service where a user can create, delete or get events with a specific label. The user also can update event information.

Stateful Services

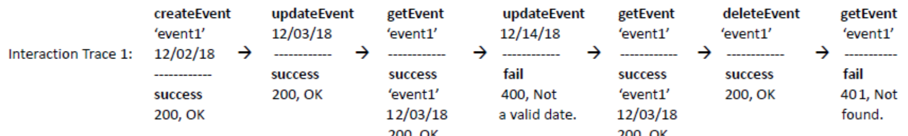

Figure: A sample interaction (request-response pair) trace.

Contributions

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- We employ two machine learning techniques to obtain a virtual service model from captured request response pairs.
- We implement our techniques in a tool and validate our approach on real services.
- We compare our techniques with a state model inference tool.

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Related Work

Leading software companies such as IBM, HP, CA, SmartBear, and Parasoft provide various commercial service virtualization tools. These tools are compared and evaluated in reports [4, 5].

Current service virtualization solutions in the literature [1, 2, 6, 7] have limited accuracy and performance and they are applicable to stateless services only.

Our previous work also provides a solution for stateless service virtualization. [3]

As far as we know, there is no previous study tackling with stateful service virtualization.

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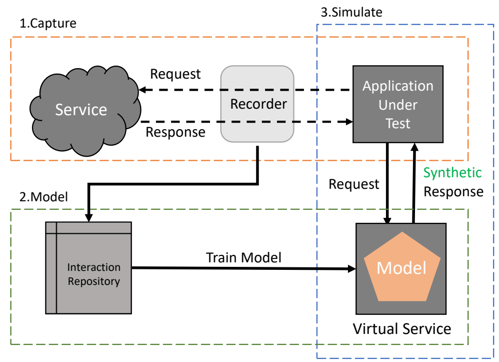
Proposed Techniques

We introduce two approaches for stateful service virtualization.

In the first technique named **Classification Based Virtualization (CBV)**, we formulate the response generation problem into a classification problem.

In the second technique named **Sequence-to-Sequence Based Virtualization (SSBV)**, we employ sequence-to-sequence models, which is a deep learning algorithm used in transformation of sequences from one form to another form.

Stateful Service Virtualization



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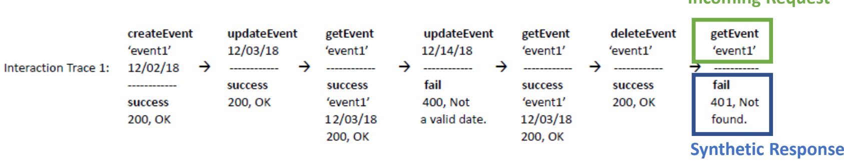

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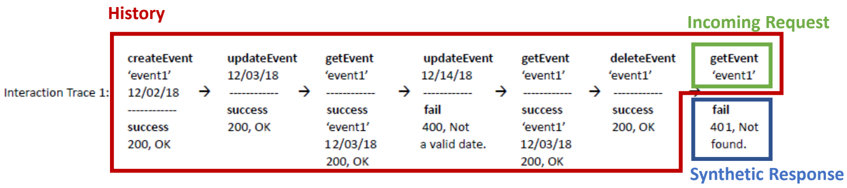

Therefore, we train a classifier that learns the mapping between the history of requests and corresponding responses.

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Attributes | Outputs

createEvent | event1 | 12/02/18 | 200, OK | getEvent | event1

[1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 ... ... 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0] --- [1, 2, 4]

Figure: An example datapoint that is provided to the classifier.

If the incoming request or the history contains a feature that is not seen in training data, it is encoded in a way that is different from all other features in the training data.

Classification Based Virtualization (CBV)

We obtain best results with Repeated Incremental Pruning to Produce Error Reduction (RIPPER) which is a pure rule based classification algorithm. RIPPER produces a set of IF-THEN rules for separation.

Note that, we predict more than one class and those classes can possibly be assigned to more than two types of labels. This kind of classification is called *multioutput-multiclass classification*.

This technique requires parsing the interactions to find request types, contents and the response to be encoded. Appropriate to use it on well-known message protocols e.g. JSON, XML.

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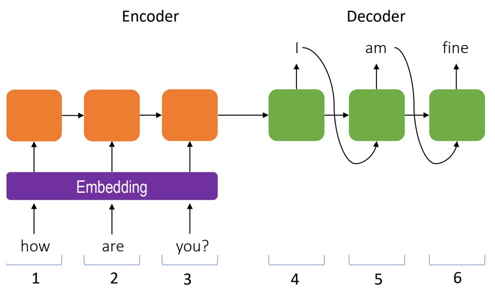

Figure: The general outline of sequence-to-sequence models consisting of an encoder and a decoder. The sequence *how are you?* is transformed to sequence *I am fine* in the figure.

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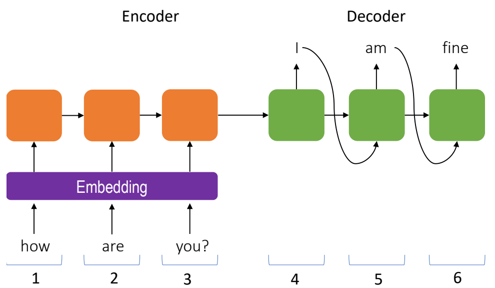

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Table: Sample inputs and the outputs used to train our sequence-to-sequence model.

Input	Output
createEvent event1 12/02/18	200, OK
createEvent event1 12/02/18 200, OK updateEvent 12/03/18	200, OK
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Correctness Evaluation

CBV:

- Exact Matching Ratio (EMR)
- Subset Matching Ratio (SMR)
- Micro averaged F-score (F_{micro})
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Performance Evaluation

Performance refers to the training time of the models for both of CBV and SSBV.

Evaluation

This is a multiclass-multilabel classification problem.

Exact Matching requires all the classes predicted for an input to be true. **Exact Matching Ratio** is number of predictions satisifying exact matching over number of all predictions.

On the other hand, **Subset Matching Ratio** is number of all correctly predicted classes over number of all classes predicted.

Micro- and macro-averaged F-scores are multiclass extensions of simple binary classification F-score.

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- We employed 5-fold cross validation for CBV and EFSM Tool.
- Experiments were run on a server with 16 GB memory and Intel Xeon E5-2630L v2 2.40GHz CPU.

Evaluation

Table: Parameters selected in experiments.

Method	Parameters
CBV (RIPPER)	$minNo = 1$
SSBV (Tensorflow)	$hidden_size = 25$ $batch_size = 128$ $layers = 2$ $epochs = 1$ $iteration = 1000$
EFSM Tool (J48)	*default*

Our primary concern in choosing those parameters is maximizing the correctness of the models.

Evaluation

Table: Correctness results of CBV, SSBV and EFSM Tool for different values of k where k is the number of previous interactions considered.

Service	k	CBV				EFSM Tool				SSBV
		EMR(%)	SMR(%)	F_{macro}	F_{micro}	EMR(%)	SMR(%)	F_{macro}	F_{micro}	Accuracy
ATS	1	76.6	79.6	0.781	0.767	78.1	80.6	0.803	0.783	92.1
Calendar	1	70.3	78.5	0.757	0.741	70.7	76.0	0.721	0.715	93.2
ATS	5	82.7	84.3	0.813	0.798	80.0	83.7	0.806	0.786	96.5
Calendar	5	81.1	84.1	0.843	0.825	71.5	77.1	0.753	0.741	97.3
ATS	10	82.7	84.3	0.813	0.798	80.0	83.7	0.806	0.786	96.5
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Virtual services created using SSBV technique are accurate enough to replace the real services when 90% or more accuracy is needed. Virtual services created using CBV technique can replace the real services when an exact match is not required and a high subset match is enough.

Evaluation

Table: Performance results of CBV, SSBV and EFSM Tool for different values of k where k is the number of previous interactions considered. Training time in format (hh:mm).

Service	k	SSBV	CBV	EFSM Tool
ATS	1	01:42	00:01	00:06
Calendar	1	02:21	00:01	00:06
ATS	5	08:51	00:03	00:11
Calendar	5	09.54	00:03	00:14
ATS	10	14:42	00:04	00:18
Calendar	10	16:19	00:04	00:19

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If time is not in the first place, SSBV method can be used to virtualize a service since SSBV is the most successful method for generating correct responses. If time is limited it would be logical to use CBV.

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- In SSBV, we employ sequence-to-sequence models for response generation.

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- infer the state machine of a service using recorded requests and responses.

QA

Thank you for listening. Questions?

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- An **interaction** is defined as a request response pair: (req, res) with $req \in Req$ and $res \in Res$.

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- Similarly, the **k history of a request** req_i is shown as:
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- A **virtual service**, $VS : H_k \rightarrow Res_{syn}$ is a function where H_k is k histories of all requests, Res_{syn} is a finite set of synthesized responses, where k equals to 1 for a stateless service.

Metrics

$$ExactMatchRatio = \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}_{E_i}(P_i)$$

$$SubsetMatchRatio = \frac{1}{np}\sum_{i=1}^{n}\sum_{j=1}^{p} \mathbb{1}_{E_{ij}}(P_{ij})$$

where

$$\mathbb{1}_A : X \to \{0,1\} \quad \text{defined as} \quad \mathbb{1}_A(x) := \begin{cases} 1, & \text{if } x = A \\ 0, & \text{if } x \neq A \end{cases}$$

E: expected outputs **P**: predicted outputs

n: the number of tests in validation phase

p: the number outputs predicted.

Metrics

$$F^c_{macro} = \frac{2\sum_{i=1}^{n}\sum_{j=1}^{p} Y^c_{ij} Z^c_{ij}}{\sum_{i=1}^{n} Z^c_i + \sum_{i=1}^{n} Y^c_i} \quad F_{macro} = \frac{1}{|C|}\sum_{k=1}^{|C|} F^{c_k}_{macro}$$

$$F_{micro} = \frac{2\sum_{k=1}^{|C|}\sum_{j=1}^{p}\sum_{i=1}^{n} Y^{c_k}_{ij} Z^{c_k}_{ij}}{\sum_{k=1}^{|C|}\sum_{j=1}^{p}\sum_{i=1}^{n} Z^{c_k}_{ij} + \sum_{k=1}^{|C|}\sum_{j=1}^{p}\sum_{i=1}^{n} Y^{c_k}_{ij}}$$

where

$$Y^{c_k}_{ij} = \begin{cases} 1, & \text{if } c_k \text{ is actually at } Y_{ij} \\ 0, & \text{otherwise} \end{cases}$$

$$Z^{c_k}_{ij} = \begin{cases} 1, & \text{if } c_k \text{ is correctly predicted at } Z_{ij} \\ 0, & \text{otherwise} \end{cases}$$

Set $C = \{c_1, c_2, \ldots, c_n\}$ is the set of all classes to be predicted.