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Detecting and Tackling the Frauds involved in Web Application

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ABSTRACT

The work entitled "Detecting And Tackling The Frauds Involved In Web Application" is a novel method for Quos metrification based on Hidden Markov Models (HMM), which further suggests an optimal path for the execution of user requests. The technique we show can be used to measure and predict the behavior of Phishing Web Services in terms of response time, and can thus be used to rank services quantitatively rather than just qualitatively. We demonstrate the feasibility and usefulness of our methodology by drawing experiments on real world data. The results have shown how our proposed method can help the user to automatically select the most reliable Phishing Web Service taking into account several metrics, among them, system predictability and response time variability. For Internet services, the presence of low-performance servers, high latency or overall poor service quality can translate into lost sales, user frustration and customers lost. The experimental results shows user click-through logs from a commercial search engine to validate the effectiveness of our proposed method. Third, the distributions of user search goals can also be useful in applications such as re ranking web search results that contain different user search goals.

Keyword: Phishing Web Service, Hidden Markov Models (HMM), re ranking web search.

1. INTRODUCTION

The Internet made the world a smaller place. Companies from all around the world may now compete over different service offerings not only with their local adversaries, but do now under a global scale. Escalating the competition and lead in industry segment can often be a matter of offering and, perhaps even most importantly, assuring the good quality of the services offered. In the Web this should be no different; controlling quality for Phishing Web Service s (WS) is done by enforcing Quality of Service (QoS) policies and assuring needed quality conditions are always met. On the user‟s side, the increased number of services means more and more offerings to choose from. Unfortunately, due to the explosive growth in the number of WSs available in the world, selecting the best WS to solve a given task has become a quite challenging task. Currently, users cast their choice based on the reviews and experiences of other users. User-created ranks are often the first resource for finding reliability information regarding a particular service, often given in terms of response time, throughput, availability, security and reliability. Dynamically composing Phishing Web Service s requires the service consumer to discover services that satisfy functional and non-functional requirements. In a dynamic environment, non-functional requirement such as WS‟s reliability in terms of response time is unlikely to be congruous with that provided by vendors in the Service Level Agreement (SLA) have considered the reliability parameters of WS‟s either as constant or suggested vendors to provide probabilistic details of the WS flow. Similarly, QoS attributes modelled as probability distribution if considered as constant or user defined function values is also not sufficient. Analyzing QoS parameters of WSs considering constant probabilistic values as baseline does not reflect precise results. Similarly, user defined function values are also not sufficient to predict future behaviour of component Phishing Web Service s. There is no standard way, however, for the users to weigh their options directly and individually, for themselves. This paper aims to fill this gap providing a standard way to measure and predict WS behaviour in terms of response time using HMM. Reliability of Service Oriented Architecture (SOA) based systems heavily depend on various underlying technologies for instance Phishing Web Service s, computing environment (CPU, Disk, and Network) and unpredictable internet. In this paper we have specifically focused on predicting Phishing Web Service ‟s behaviour in terms of Response Time (RT). For other factors such as CPU, disk or network one can find solutions. In HMM, the number of hidden states to be used is unknown. Usually, based on domain knowledge there is only some guess about it. For example, in case of web servers, network load balancing distributes incoming users‟ requests among multiple web servers to handle more traffic and faster response. In this case multiple web servers can be different hidden states responding to users‟ requests randomly. These states are hidden from the users‟ and respond to their requests randomly based on their execution. However, there are two things to consider:

- Phishing Web Service s are owned and hosted by other organizations. So users have way to analyze them directly.
- These hidden states can neither be discovered or guaranteed with traditional exhaustive testing nor can be relied on service providers‟ exposed parameters defined

Therefore, it is more challenging to analyze or predict behaviour of hidden states with respect to response time. To tackle this challenge, in this paper we present a novel approach. It first computes the behaviour of internal structure of WS using the HMM. Later it combines the status of underlying hidden states to compute the overall behaviour of each component Phishing Web Service . Approach defined here can also be utilized to find an optimal path to accomplish users‟ requests. This can be achieved by building a directed graph among various hidden states. In comparison to existing strategies, our contribution in this paper can be summarized as follows:

- Predicted Phishing Web Service ‟s behaviour by predicting the status of underlying hidden states in terms of Response Time (RT).
- Selected optimal WSs and an optimal path at runtime for executing user request by identifying the status of underlying hidden states.

2. RELATED WORK

2.1 Architecture-based Dependability Prediction for Service-oriented Computing

In service-oriented computing, services are built as an assembly of pre-existing, independently developed services. Hence, predicting their dependability is important to appropriately drive the selection and assembly of services, to get some required dependability level. We present an approach to the dependability prediction of such services, exploiting ideas from the Software Architecture- and component-based approaches to software design. In the Service-Oriented Computing (SOC) paradigm, an application is built as composition of components and services (including both basic services, e.g. computing, storage, communication, and “advanced” services that incorporate some complex business logic) provided by several independent providers.

2.2 QoS Analysis for Phishing Web Service Composition

The problem of composing services to deliver integrated business solutions has been widely studied in the last years. Besides addressing functional requirements, services compositions should also provide agreed service levels. Our goal is to support model-based analysis of service compositions, with a focus on the assessment of non-functional quality attributes, namely performance and reliability. We propose a model driven approach, which automatically transforms a design model of service composition into an analysis model, which then feeds a probabilistic model checker for quality prediction.

2.3 Composing Phishing Web Service s: A QoS View

An Internet application can invoke several services a stock-trading Phishing Web Service , for example, could invoke a payment service, which could then invoke an authentication service. Such a scenario is called a composite Phishing Web Service , and it can be specified statically or established dynamically. Dynamic composition of Phishing Web Service s requires service consumers to discover service providers that satisfy given functional and non functional requirements, including cost and QoS requirements such as performance and availability.

3. PROPOSED SYSTEM

A novel method for Quos metrification based on Hidden Markov Models (HMM), which further suggests an optimal path for the execution of user requests. The users can weigh their options directly and individually, for themselves. We use Hidden Markov Models for Building a directed graph among hidden states of component Phishing Web Service s used in composition. Analyzing the current status of each vertex of directed graph i.e., underlying hidden states. Predicting hidden states behaviour in terms of response time during nth time interval t. Finally, selecting optimal Phishing Web Service s used in composition based on hidden states behaviour. A hidden Markov model (HMM) is a statistical Markov model in which the system being modelled is assumed to be a Markov process with unobserved (*hidden*) states. An HMM can be presented as the simplest dynamic Bayesian network. The mathematics behind the HMM were developed by L. E. Baum and co-workers. It is closely related to an earlier work on the optimal nonlinear filtering problem by Ruslan L. Stratonovich, who was the first to describe the forward-backward procedure.

In simpler Markov models (like a Markov chain), the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters. In a HMM, the state is not directly visible, but the output, dependent on the state, is visible. Each state has a probability distribution over the possible output tokens. Therefore, the sequence of tokens generated by an HMM gives some information about the sequence of states. The adjective 'hidden' refers to the state sequence through which the model passes, not to the parameters of the model; the model is still referred to as a 'hidden' Markov model even if these parameters are known exactly.

Hidden Markov models are especially known for their application in temporal pattern recognition such as speech, handwriting, gesture recognition, part-of-speech tagging, musical score following, partial discharges and bioinformatics.

4. SYSTEM MODEL AND PARAMETERS

HMM is a powerful statistical tool for modelling generative sequences that can be characterized by an underlying process generating observable sequences. Word hidden specifies that internal structure of the underlying system is hidden from the observer. Observer does not know in which state system may be in, but has only probabilistic insight where it should be. In HMM, one does not know how many hidden states to use. Usually, based on

domain knowledge there is only some guess about hidden states. We have discussed in detail about WS hidden states. Later training algorithm will find out how to connect these hidden states. HMM can solve three fundamental issues i.e., Evaluation, Decoding, Training. Using HMM to measure and predict WS behaviour with respect to response time, our model consists of a two step process. First step will require us to train the model to find optimal HMM parameters i.e., A, B & π, such that model best fits the training sequence. Training sequence in our model can be exploited by recording and labelling response time of a Phishing Web Service at regular intervals of time. Baum-Welch algorithm a particular case of EM can be used to train the model. It iteratively improves the basic model which provides convergence to local optima, whereas second step, first requires us to compute current state of the system. Then based on current state, future behaviour of the system is predicted. This can be computed using VITERBI algorithm. Based on above two steps, for selecting an optimal WS and an optimal path for executing user requests our strategy can be further divided into following steps:

- Building a directed graph among hidden states of component Phishing Web Service s used in composition.
- Analyzing the current status of each vertex of directed graph i.e., underlying hidden states.
- Predicting hidden states‟ behaviour in terms of response time during nth time interval t.
- Finally, selecting optimal Phishing Web Service s used in composition based on hidden states‟ behaviour.

5. Exemplary Scenario

To analyze the behavioural pattern of hidden states, we have Selected a weather forecast WS with best rank. More than 500 threads are used in parallel in a distributed environment. As in HMM, one does not know how many hidden state to use, so we have supposed that target WS is running on a cluster of web server, containing 2 web servers. We found that 9 percent of the overall result was with observation symbol „„C‟‟‟ as shown in Fig. 5.1. Later, when we further scrutinized the result by training the model, we have found that 8.2 percent from 9 percent failures were caused by web server1 whereas only 0.8 percent failures were originated by web server2. This shows that probability of receiving failure when web server1 executes the results is more than web server2. The analysis shows that at runtime behavioural patterns of the hidden states can be utilized for selecting optimal Phishing Web Service s among the list of functionally equivalent Phishing Web Service s. Hidden states with observation symbol A of different WSs can be connected at runtime to process user‟s request. In the next step we will explain the process of building a directed graph among the hidden states of different Phishing Web Service s used in composition.

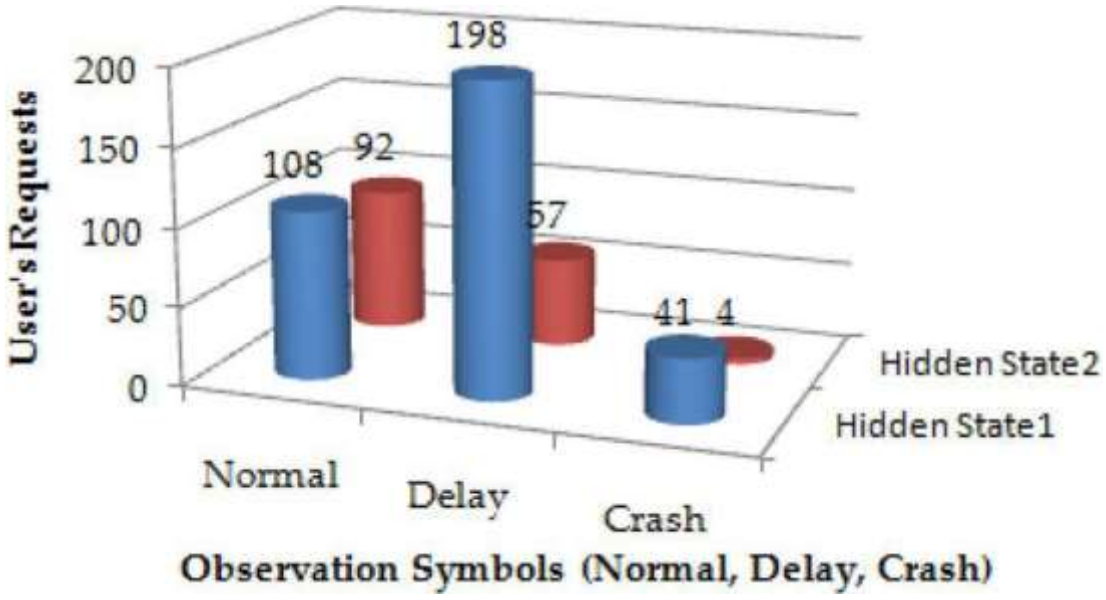

Fig.1 Hidden states observation patterns in terms of number of requests

6. CONCLUSION

The System probabilistic model for predicting response time of Phishing Web Service and then selected an optimal Phishing Web Service at runtime from the list of functionally equivalent Phishing Web Service s. To know the probabilistic insight of WSs we have used HMM. In our model we have assumed that WS is deployed on a cluster of web servers and sometime the delay or crash during WS invocation is because the bad node in sever clustering responds to users‟ requests. With the help of HMM we have predicted the probabilistic behaviour of these web servers and then selected the WS based on their probabilistic value.

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