A Novel Technique for Atomic Web Service Reliability for Service Oriented Architecture

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Abstract : To address the challenges in prediction of atomic web service reliability for the Service Oriented Architecture (SOA), clustering based approach called the Dynamic Clustering (DCLUS) is proposed. The DCLUS is based on recent work reported called CLUS. The novelty in DCLUS compared to CLUS technique is use of dynamic width clustering technique. k-means clustering method exploited for the users and services clustering. However, due to the limitations of k-means, the dynamic width clustering is used to optimize the performance of clustering and hence the prediction accuracy. The proposed DCLUS model for the reliability prediction of atomic web services that estimates the reliability for an ongoing service invocation based on the data assembled from previous invocations. With the aim to improve the accuracy of the current state-of-the-art prediction models, user–, service– and environment–specific parameters of the invocation context is incorporated.

Keywords: State-of-the-art, K-means, Service Oriented Architecture.

I. INTRODUCTION

The Service Oriented Architecture enables the web services to compose atomic services by using advanced functionalities. There is vast majority of web applications which follows a certain set of rules and principles defined by Service Oriented Architecture (SOA).While constructing composite services, it is essential for the developer to select high quality atomic service candidates. The application quality relies on both functional and non-functional qualities of the selected candidates. Functional properties include the working of your service, functionalities, constraints etc. and Non- functional properties include response time, availability, and reliability. Reliability is the excellence feature of a Web service that represents the degree of being capable of maintaining the service and service quality. The amount of failures per month or year represents a measure of reliability of a Web service. In another logic, reliability refers to the assured and ordered delivery for messages being sent and received by service requestors and service providers. The more reliable the messaging, the more tangible the service oriented solutions. It introduces a flexible system that guarantees the delivery of message sequences supported by comprehensive fault reporting[1]. Hence, to create an efficient composite application, the developer should be provided with reliable information on both atomic services' functionalities and their non-functional dependability attributes. The atomic web services reliability is one of the most challenging tasks while constructing QoS-aware composite work-flows based on SOAs. Since service requests, besides required functionality, include required non-functional parameters, they must be taken into account during service composition procedure. These parameters however concern, in general, the quality of required service, which vary in time and depends mostly on current state of computer communication system used as a backbone for complex service delivery.

A strategy to overcome the challenge of reliability assessment is to obtain partial but relevant history invocation sample and to utilize prediction algorithm to estimate reliability for missing records. To predict the accuracy, collaborative filtering provides accurate recommendations in static environment.

To predict the reliable web service various methods have been used but there are certain limitations in techniques. Few can meet the requirements of being efficient and scalable for web service selection.

The following sections are organized as follows: Section 2 will describe related works in the field of Prediction of Web Service Selection based on Recommendation. Section 3 describe the Existing System. Section 4 shows the results of Existing System and Section 5 will outline the approach taken by the proposed system. The framework will be evaluated in this section. Finally, Section 6 will describe concluding thoughts and ideas in this area.

II. RELATED WORK

This study is used to show how the different methods can be also used in Prediction of Web Service. Ten papers have been studied which uses various methods, which are described as follows:

In paper "A Privacy Preserving QoS Prediction Framework for Web Service Recommendation",[2] Jieming Zhu.Et al., focuses on privacy preserving framework which applies data obfuscation techniques and based on these data, develops two approaches based on Privacy-Predicting QoS. This Privacy Preserving framework can be applied to both neighborhood-based collaborative filtering approach, i.e.,User and Item based Pearson Correlation Coefficient(UIPCC) and model-based collaborative filtering approach, i.e., PMF. Here the author revamps these technique and proposed new approachES WHICH ARE P-UIPCC AND P-PMF.

The key of P-UIPCC that it uses both user based methods and item based methods respectively. It computes the similarity between users and similarity between services. Pearson Correlation Coefficient(PCC) is recycled for resemblance major.Pearson's correlation coefficient is the covariance of the two variables divided by the product of their regulardeviances. The goal of P-PMF is to map users and services into a joint latent factor space such that each observed entry of QoS matrix is captured as a Linear Product of Corresponding latent factor.

The author concludes with the effective values are gained in case of P-UIPCC and P- PMFas compare to its counterparts
The Paper "Scalable and Accurate Prediction of Availability of Atomic Web Service",[3] proposes a formal model LUCS (service Load, User Location, service Class, Service Location) for predicting the availability of atomic web services which enhances the current State-of-the-art model for Recommendation System. Based on prior requests of user's and services geographical location, service load and service's computational requirements it estimates the service availability. By using this method the complexity is removed as it utilizes contextualized information about user and services. LUCS deals with the accuracy and scalability of prediction. LUCS achieves better prediction as compare to IPCC, UPCC and Hybrid model. But at the same time LUCS does not include some user specific parameter which might impact the Prediction. Also its application is dependent on the availability of its input parameters hence certain service provider may not be willing to share the data.

You Ma [4] Proposes two approaches for service recommendation: 1) to tackle the problem of Unknown QoS property values TBQP (Tensor based QoS Prediction) method is used. 2) To address the problem of evaluation of overall QoS, OQPUP (Overall QoS Prediction based on user preference) is used.In TBQP, the multi-dimensional QoS data is modeled as a Tensor, often referred to as QoS-Tensor. It is nothing but any dimension which considers all QoS data integral and uniformly. The Tensor is decomposed based on Euclidean distance. In OQPUP, obtains preference of users by using user Preference Learning. It is a mining process in which user preferences based on different QoS Properties are collected. The collection of preferences is usually done on the Historical Rating the user is assigned to Web Services.

In "A Highly Accurate Prediction algorithm for Unknown Web Service QoS Values",[5] Proposes HAPA (Highly Accurate Prediction Algorithm) for unknown web service QoS values. Here the author shows an important difference between subjective and objective data. Subjective data are the data which comes directly from user and Objective data includes service response time and reliability. For the former, two high similar users often gives similar values for an item while it is not the case for objective data. So HAPA come into picture.It states that if two users share a high similarity then their similarity will hardly fluctuate with their future invocations of more number of web services. In same way, If two items share a high similarity then the similarity will hardly fluctuate with their future invocations by more number of users.HAPA is built for the Prediction of unknown web service based on these characteristics.HAPA is Collaborative Filtering based algorithm which concretely consists of user based and item based HAPAs. But here author has used both things combinational. It makes prediction more accurate. Here the unknown QoS values is calculated from all the prediction values made by every similar user.

Yilei Zhang [6] proposes a technique called OPred(Online performance Prediction). To address the performance of web service status and network environment which become variable over time , this becomes an important task to predict the performance of Service Oriented System. To address this an online performance prediction framework OPred is used. OPredshapes feature models and services time series analysis techniques on feature trends to make performance prediction. Here the author uses a set of latent features to precisely predict the performance of web service.

In [7] Qi Yi et al., proposes TNR-MF(Trace Norm Regularized Matrix Factorization) algorithm. It aims to discover a QoS matrix from a subset of observed QoS entries. The entries are obtained from Historical user-service interaction. TNR-MR obtains a low rank structure and clustered representation of QoS data by indexing users with rows and services with columns that forms a matrix of QoS data. It is modeled as a general matrix completion problem. This algorithm found to be effective method for accurate prediction.

In [8] Aviv Segevet al., proposes a Hybrid Recommendation Model which combines collaborative filtering and content based approach. It associates rating and content data with newly introduced variables that represents user preference. This technique has a set of latent variables that directly describe substantial preferences, which cannot be obtained directly. The preferences are statistically estimated using Expectation Maximization (EM) which recommend better web service.

Xiong Luo et al., [9] proposes a combination of Fuzzy Neural Network and Adaptive Dynamic Programming(ADP). This approach extracts fuzzy rules from QoS data and employs ADP methods to parameter learning of fuzzy rules. FNN not only extracts fuzzy rules from data to express dynamic property of system but also adjusts parameters of network during learning process to enhance the adaptability of network. By using this technique reduction in computation time is achieved.

In [10] Wenlong Zhu et al., proposes an advanced fully polynomial time approximation scheme to calculate Pareto Optimal set, where each solution is not dominated by others. It presents an approach for web service selection for multiple users requesting the same workflow. It balances the computation cost and precision of output by regulating global error bound and unequal local output to calculate Pareto optimal set. Here they first normalize the workflow and then the algorithm is being applied.

In [11] T. H. Akila et al., proposes a traffic efficient multiobjective method which affects heterogeneous selection requirements and achieves global optima for linear and combinational selection requirements. For internal traffic MR algorithm is used and for external traffic ZipF and Pareto are used. These are mainly used to avoid the congestion. Here another middle agent is used to ease the reducer workload. By using this technique traffic congestion is handled efficiently and effectively for multi objective selection requirements.

III. EXISTING SYSTEM

This include the overview of existing architecture

3.1 System Architecture

Below figure shows the working flow or architecture of existing CLUS method [12]. In CLUS, aiming to improve the prediction accuracy User, Service and Environment specific parameters which determine service invocation based on K-means Technique.

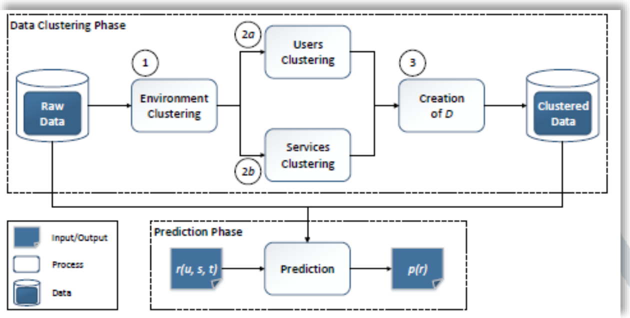

Fig 3.1 Existing System

The overview of CLUS, model for prediction of atomic web services is shown in fig 1. As can be seen in the figure, reliability prediction process is consisted of two separate phases: data clustering phase and prediction phase. Firstly, the time windows associated with environment conditions are clustered according to the reliability performance fetched from past invocation sample. Then users and services are clustered. Finally a three-dimensional space D containing the clustered data is created. Once the clustering phase is done, prediction of atomic services reliability is performed. The prediction is done based on RMSE values.

IV. RESULT OF EXISTING SYSTEM

4.1 Introduction to Dataset

Web service QoS dataset is used to evaluate [13].This dataset describes real-world QoS assessment results from 339 users on 5,825 Web services.

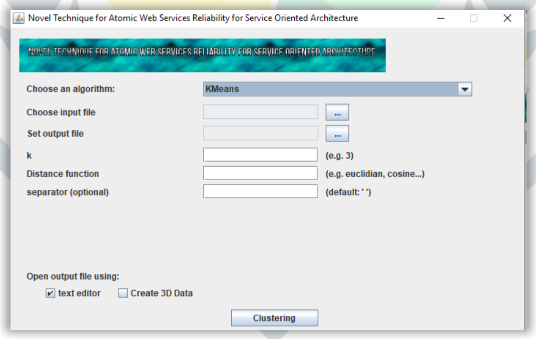

Fig 4.1 Choosing the Algorithm

Here the required algorithm is selected. The required input and output file is to be selected. The number of iteration is defined by k.

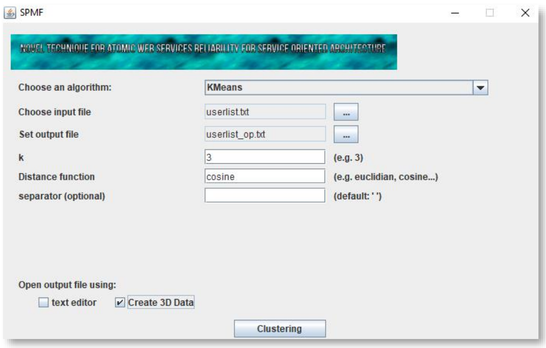

Fig 4.2 Choosing Input and Output file

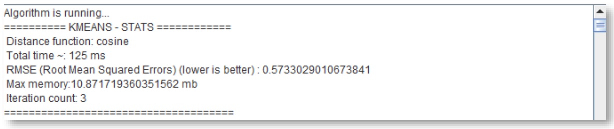

Fig 4.3 Prediction Based on RMSE values

V. PROPOSED SYSTEM

There are certain limitation of Existing System which uses K-means algorithm. K-means exploits the data. To overcome this limitation DCLUS approach is proposed. DCLUS uses Dynamic clustering method.

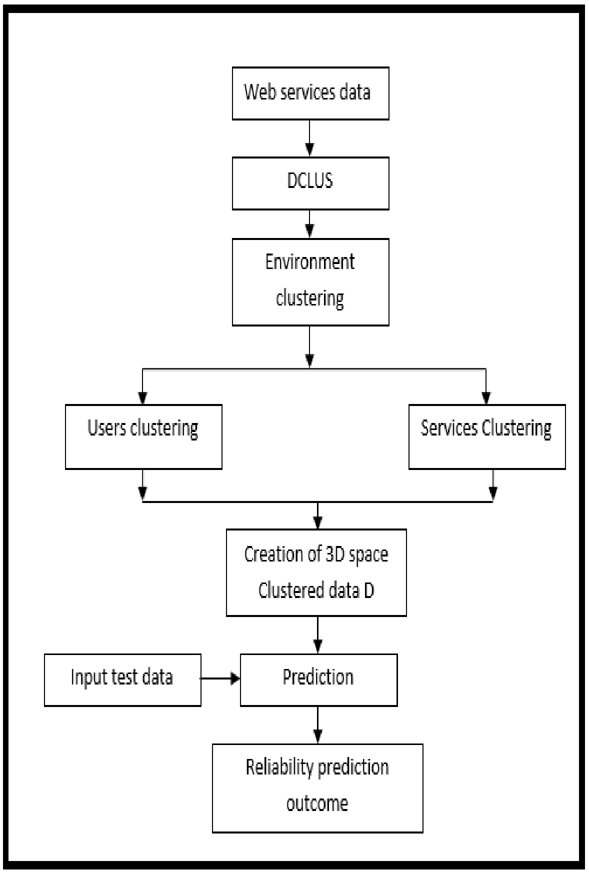

Fig.5.1 Proposed System

The proposed DLUS model for the reliability prediction of atomic web service that estimates the reliability for an ongoing service invocation which aims to improve the accuracy of the current state-of-the-art prediction models i.e user, service and environment specific parameters of the invocation context are incorporated.
The core idea behind a Dynamic Clustering (DC) system [14] is that for each decision is taken, current battle situation is examined. This allows to adapt the limit at which data is collected so far, as well as to change how it classifies that data on-the-fly, because it's always reexamining the original data. The basic type of collaborative filtering are:
1] Memory Based Collaborative Filtering- This technique extracts the information or patterns by statistically correlating the data obtained from various sources.
2] Model Based Collaborative Filtering-Uses complex techniques such as machine learning or data mining to recognize complex patterns using Training Data and then use model to make Predictions on real data.
A high level overview of Proposed System DCLUS, model for prediction of atomic web services is depicted in Fig.5.1. As can be seen there are three parameters have been used for clustering of data: Environment clustering, User clustering, Service clustering.
1] Environment–specific Parameters - For the purpose of evaluation only Service Load is considered as an Environment parameter. Service Load can be defined as the number of requests received per second. As there are certain Load Variation of Services during the full day, arbitrary number of Time Windows have been used.
2] User-specific Parameters - User-specific Parameters include a variety of factors which impact the reliability of service such as user's location, network and device capabilities, and usage profiles.
3] Service–specific Parameters - Service-specific Parameters are related to the impact of service characteristics on reliability performance. It includes service's location, computational complexity and system resources (e.g. CPU, RAM, disk and I/O operations).
4] 3D Space D - 3D Space is used to make scalable and accurate reliability predictions for future invocations. The data is stored in the form of three dimensional space D[u,s,e] where each dimension u, s and e is associated with one group of parameters.

5] Prediction - To Evaluate Prediction accuracy Root Mean Square Error (RMSE) is used. It computes the Quadratic Scoring rule which represents average magnitude of errors.

$$\text{RMSE} = \sqrt{\sum \frac{(y_{pred} - y_{ref})^2}{N}}$$

VI. CONCLUSION

Prediction based on Recommendation plays a vital role in everyday life. It helps to understand how service selection of atomic web services is done. The limitation of K-means clustering is that it exploits its users and services. It can be overcome by DCLUS technique, which uses Dynamic Width Clustering Algorithm. DCLUS estimates the reliability for an ongoing service invocation based on the data recorded from previous invocations which is explained in Proposed System.

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