Novel Clustering-Based Web Service Recommendation Framework

Priya Bhaskar Pandharbale, School of Computer Engineering, KIIT University (Deemed), Bhubaneswar, India
https://orcid.org/0000-0003-4547-7788

Sachi Nandan Mohanty, Department of Computer Sc & Engineering, Vardhaman College of Engineering (Autonomous), Hyderabad, India
https://orcid.org/0000-0002-4939-0797

Alok Kumar Jagadev, School of Computer Engineering, KIIT University (Deemed), Bhubaneswar, India

ABSTRACT

The quality of web services is measured or derived using various parameters like reliability, scalability, flexibility, availability, etc. However, the limitation of these methods is that they are producing similar web services in recommendation lists. To address this research problem, the improved clustering-based web service recommendation method is proposed in this project. This approach is mainly to produce diversity in the results of web service recommendation. In this method, functional interest, QoS preference, and diversity features are combined to produce the unique recommendation list of web services to end-users. To produce the unique recommendation results, the researchers proposed a web service classify order that is clustering based on web service functional relevance such as non-useful pertinence, recorded client intrigue importance, potential client intrigue significance, etc.

KEYWORDS

Clustering, QoS Prediction, Recommendation, Various Width Clustering, Web Service

INTRODUCTION

To expend an administration, the client sends a solicitation and acquires a reaction from the utilizing administration. Fundamentally, administrations can be devoured in two distinct ways. They can be utilized as straightforward administrations that give an interface to get information sources and return yields or they can be utilized as segments that can be incorporated into business forms. The first type of usage is termed individual use and the second type of usage is called process use. This research work deals with recommending services concerning the individual case. To discover an administration for individual use, a user can utilize a notable internet searcher, for example, Google, Yahoo, or Baidu. In any case, much of the time, the particular administration web indexes that can give 'great' benefits yet additionally can help to find other fascinating administrations are preferred by the user. Also many service portals such as XMethods, Binding Point, WebServiceX.NET, Web Service List, StrikeIron, Remote Methods, and Woogle and serve crawlers so as Seekda also Embrace Registry were explained as explicit tools for assisting users in searching and invoking web service for individual use Zheng et al. (2011).

To support users to utilize services for a specific use, newer strategies proposed by various authors get into report information so as Web service specifications, Quality of Service (QoS) moreover

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semantic theories of services making recommendations not considering information that uncovers client concerns, for example, utilization information. What's more, they can meet content based on equivalent words and polysemy issues. Any of them are tiresome and any others need endeavors of a user, for illustration, rating WS as said by Galli (2020) the principle of continuous technological improvement meet inherent objectives would be the focus.

Though Web Service technologies and Service-Oriented Computing (SOC) promises about loose coupling among parts, dexterity to react to changes in necessities conveyed registering and lesser progressing ventures, web service is not shared and reused as expected Wang et al. (2004). One of the reasons that impede the usage of such technologies and SOC is that efficient web service discovery presents many challenges Garofalakis et al. (2006). Recommender systems (RS) are one tool to help bridge this gap Pazzani & Billsus (2007). Various mechanisms are being employed to create RS Brusilovski et al. (2007) and the common systems include two main classes such as content basis furthermore collaborative filtering schemes (Ma et al. 2007). Content basis RS does the matching between textual information of a particular product with the textual information representing the interests of a customer. Collaborative filtering methods perform the use of designs in customer grades to recommend Jagadev and Mohanty (2018). Both types of RS expect notable data resources under the order of user ranks and product features; hence they are not able to generate high-quality recommendations Pandharbale et al. (2020)

Innovation is the idea that turns into reality (Tikhomirova, 2020) considering this the work proposes methods to service discovery that are lighter than those based on semantics that can be a feasible way towards the realization of service-oriented applications. It also attempts to settle the difficulties of forecasting QoS values by combining Pearson similarity and the Slope One method and a simple enhanced algorithm for ranking services considering users' requirements are better than the existing complicated algorithm. Therefore, the basic purposes of this research are:

The work focuses on proposing a new approach to build a semantic kernel consisting of semantically similar Web services using the various widths clustering and merging method. It will help to improve the quality of the predicted QoS significances of Web services as well as the designing of new efficient and scalable algorithms for various widths clustering-based web service reliability for the recommendation systems that is the knowledge creation facility (Omamo et al., 2020).

RELATED WORK

In this area, we quickly examine a portion of the exploration works identified with finding clustering and Web services recommendations. Albeit different methodologies can be used to recognize and discover Web services on the web, we have coordinated our assessment on execution eminence and exposure issues. Each web service is related to a WSDL description that includes the depiction of the service. Halevy et al (2004) suggested that Web services internet web index Google is reasonable for giving Web services closeness search. In a few cases, their gadget does not adequately acknowledge data types, which for the most part uncovers significant data regarding the operation of Web services. Liu in addition to Wong Chen et al. (2006) executes substance mining systems to concentrate highlights, for example, service content, setting, hostname, and name, from Web service portrayal documents to bunch Web services. They proposed a consolidated component burrowing, what's more, the clustering approach concerning Web services as a predecessor to exposure, needing to assist in constructing a web search contraption to the edge and push non-semantic Web services. The use of ANN is another aspect to solve the problems for a recommendation based on forecasting property. In neural network forecasting, usually, the results get very close to the true or actual values simply because this model can be iteratively is adjusted so that errors are reduced because of its effective pattern classification capabilities (Bhardwaj, 2020).

Elgazzar et al. (2010) exhibited a relative technique, which conveys WSDL reports to build the non-semantic website composition appearing. They comprehend singular segments in WSDL records as their segment and organize web services into worth based social issues. The clustering impacts compartment is utilized to build up the idea of web service record data.

Abramowicz et al. (2007), states the execution of working for Web services ordering and clustering. The service sifting system depends on consumers what's more, application shapes that are portrayed working OWL-S (Web Introspective philosophy Language for Services). The adequacy of the channels depends upon a clustering evaluation that considers services identified with the pack. The goals of this event planning policy are to deliver performance time and to promote the culture of the put beyond data. Different relative strategy Wishart et al. (2005), centers on Web administration disclosure with OWL-S. The OWLS is first united with WSDL to address association semantics before using a clustering figuring to signify the sums of heterogeneous services. Finally, a client question is energized against the pack, to re-establish the sensible services. Regardless, the creation and upkeep of reasoning may infuriate and include an enormous measure of human exertion Platzer et al. (2009).

Web service notoriety speaks to an instrument depending on inputs given by shoppers/software specialists to gauge Web service dependability. It is displayed as a vector of complete clients/programming overseer's appraisals for a web administration. Moreover, the phenomenal rating sources of info are combined to find a service supplier's reliability. All elements analyzed, the info is made out of the accumulated quality of service (QoS) data gathered of execution looking at and these demands the grip interference similar that require the purchaser's intervention like the expense of precision that can't be watched. As per the QoS data appropriated and a customer inclination counting required QoS estimations, the QoS library will figure a general rating for each web organization that matches the purchaser's inquiry demand. At that point, the customer will choose the web service with the most raised rating (Wang et al. 2014). By far most of the proposed notoriety methodologies utilize a focal library to gather and share the purchaser's criticism. Since this focal engineering is liable to disappointment, different works dependent on shared web services are proposed to manage a decentralized notoriety component Vu et al. (2005). A service supplier that gives attractive service may become inaccurate or incorrect charges from uncalled for or resentful raters. One of the difficult problems is protecting web service reliability from these mixed up information sources. A couple of instruments have been proposed to distinguish and oversee corrupt reactions by using submitted watching administrators channel customers' appraisal Malik and Bouguettaya, (2007), or communitarian filtering methodologies subject to circulated courses of action Wang et al. (2010). Recorded as a hard copy, a grade of service is a vector of trademark characteristics. The figured reputation rating may be a twofold worth (trusted or depended), a scaled entire number (for example 1-10), or on the other hand on an energetic scale (e.g., [0, 1]). Thusly, the satisfaction level of web services is normally a sorted out numerical worth, keeping an eye on quantitative reputation, used for dynamic services masterminding and decision.

Maximilien et al. (2002, 2005) proposed a multi-master-based structure where managers help quality-based organization certification using an office to disperse reputation and support data. Every go-between services are independent yet furthermore co-operate with various pros to accumulate various suppositions and along these lines intensify its data to improve its fundamental pro.

Liu et al. (2004) executed the calculation about how to solidify undeniable QoS estimations to get a sense as a rule rating for a web service. The proposed reputation can be portrayed as the standard organizing given to the organization by the end-client.

Majithia et al. (2004) think about appraisals of services into distinct environments and a coefficient (weight) remain associated with each fitting condition. This coefficient shows its centrality to an appropriate method of customers. In light of that coefficient, they executed a system to register the reliability rate as weight down the total of explorations for service.

Wishart et al. (2005) present a developing variable for the notoriety score, which is related to the majority of the assessments for administration. The process has implemented the notoriety score as the weighted run of the mill of all appraisals of an administration got from clients, including a solidification factor tending to the weight joined to the majority of the evaluations or the organization.

Trust and reputation instruments are relentlessly related. Web service reputation can be considered as a social occasion of evaluation for an organization from buyers/programming directors, while web administration trust addresses a changed and one of a kind choice mirroring a web service Malik, and Bouguettaya (2007). Right now, a few sorts of research in the area of confidence and notoriety focuses are assessed. We identify with for test the work (Wang & Vassileva 2007) that executed the procedural to look at the dependability of every buyer, which at last encourages the web services determination procedure considering criticisms detailed by confided in clients than others.

Web service framework has been comfortable with the fundamental of-utilization web service revelation. It may be seen as a go-between that holds the meta-information and vault data about its part services and speaks to space explicit learning Liu et al. (2010). Among the Network based methodology, we presented for illustration the work Elgazzar et al. (2010) that has implemented a framework amassed a service confirmation approach dependent on super-experts. These specialists share their information about the services they have collaborated with, which is tremendous for various administrators to make the helpful attestation of services. This is to keep up frameworks and gather framework-based notoriety for a service dependent on the completion of all framework individuals that have relative interests and judgment criteria.

Kang et al (2015) illustrated a new technique for recommending web services to clients. In this authors incorporate user's probable QoS recommendations and also various quality features of user's interest in Web services depending on exploring the user's history of the Web Service.

Gong et al (2013) give service recommendation an approach is recognized comparatively URPC-Rec (User Relationships Preferences Clustering also Recommendation). In this algorithm, requested services depending on their history behaviors used by clusters and after that specification is given.

Liu et al. (2004) developed a method to overcome the issue of many user web service collections. The system recognizes the removed multi-QoS costs based on historical QoS activity of the user as well as after that select generally utilized technique for multiple users by our immediate competition technique.

Lo et al (2012) presented a new concentrated QoS expectation structure including location-based regularization (LBR). The designer originally calculated up in the most popular Matrix Factorization (MF) approach for conditions that are not provided in expectation.

Wenmin et al (2011) gave a method to solve the issue of the "ensured" quality. To overcome this issue author given a history record-based service minimization technique considered Hire Some. The integrity of service arrangement is maximized by this technique as well as by exploiting a web service's QoS history records as opposed to building up the given QoS qualities embraced by the supplier of the service.

Li and Yu (2012) evolved an effective greedy algorithm to get close ideal assortment relying upon positioning along with the linear time and space complexity respectively size of the graph.

Alrifai et al. (2010) gave a public, genuine, and dynamic QoS calculation method for web services. Web services are chosen by executing and also by observing with a QoS value prediction.

Garanayak et al. (2019, 2020) presented the recommender systems using item-based collaborative-filtering techniques and K-means. The work helps the user to give appropriate item recommendations. The system helps the students seeking admission to the undergraduate program in the top ten IIT India using the recommendation.

Majhi (2018), in this work author, has presented the breast cancer classification using a feed foreword neural network trained by a sine-cosine algorithm. The proposed approach is very robust, effective, and gives better correct classification as compared to other classifiers.

METHODOLOGY

Contributing to the existing Web Service Recommendation approach with the proposed algorithm called Clustering-based system to overcome the limitation of web service recommendation. The advanced strategy will be used to develop the production of the system. This system is shown in figure 1 clustering-based web service recommendation(CWSR). All the functionality used by Web service discovery(WSD) is used by the proposed method CWSR but also uses one extra functionality that is clustered data. Below define all functionality of the method.

Functional Evaluation

The functional appraisal can be furthermore isolated into two sections: Functional Estimation 1 moreover Functional Estimation 2. Functional Estimation 1 considers the result of the client's chronicled expectation with Web services apply controlled to a premise-based equivalence criterion. The substance-based identity is procured by object closeness. This product simply recognizes Web services that are represented by the WSD(Web Service Discovery). All things considered, it is anything but difficult to stretch out our work to deal with different sorts of Web services. The client's real interest can be mined from his/her very own affiliation use or requesting history. Functional estimation 2 predicts the client's potential interest and diagrams its congruity with Web services by using shared isolating based customer comparability. This comparability is estimated depending on the administration summon history of all administration clients.

Non-Functional Evaluation

Think about that m QoS structures are worked for estimating the non-utilitarian quality of USi, its QoS vector is meant by $\boldsymbol{SWi}$, i.e., $\boldsymbol{SWi} = (qi,1,qi,2,\ldots,qi,m)$, where qi,j expresses the value of the jt quality standard. For the most part, there are two types of QoS measures. A QoS model is seen as negative if the bigger the worth, the lower the quality, (e.g., Cost besides Reaction Time). Then again, if the more noteworthy the worth, the QoS measure is seen as positive (e.g., Accessibility and Unwavering quality). Evaluations of different QoS criteria should be built up to a tantamount arrangement for different assessment purposes. While previously uniformity, implement the measurable strategy (i.e., Pauta Paradigm methodology) to before procedure the QoS esteems ahead of time to expel the exceptions. Here, change each QoS standard incentive to a genuine number somewhere in the range of 0 and 1 by contrasting it and the base and most extreme estimations of the QoS basis among all accessible Web administration up-and-comers. After such standardization preparing, the more noteworthy incentive for the quality, a model implies more excellent quality.

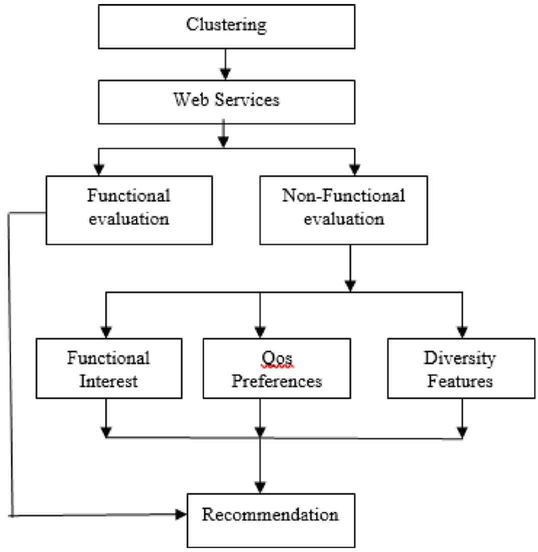
Recommendation

To recommend web service we use web service graph construction and service ranking method. A web service graph $G = (V,\mathrm{E})$ is an undirected weighted graph comprising of a lot of hubs V and a lot of edges E, wherein a hub means a Web service competitor, i.e., $\upsilon i = \mathrm{US}i$, and an edge indicates that the associated hubs are comparable. $V = K$ is the number of hubs (i.e., Web services) in the chart. Be that as it may, here not all the Internet services in the Internet service pool are used for dealing with the Internet proposal diagram. Fundamentally, the Internet services with explicit congruity to client interest are utilized. In web service ranking, calculate the score for each node in the graph. Then as per score we provide a rank to each node and showing top k node. Here node represents the web service Input Dataset

1) *User set*
2) Web service Set
3) QoS Matrix

$$userSimda,ab = 2\times|USab|/|Sda|+|Sdb| \tag{1}$$

Figure 1. System Architecture



Where Sda and Sdb are the numbers of Web services appropriated by the user da also db sequentially, $USab$ denotes the collection of Web services utilized with both da and db, i.e., $USab = Sda \cap Sdb$. If $USab = 0$, then $use(ua, ub) = 0$.

$$(\mathrm{US}i,\ \mathrm{US}j) = \varphi texSim + \phi opSim \tag{2}$$

Where $texSim = \cos \boldsymbol{wi}, = \boldsymbol{wi} \bullet \boldsymbol{wj} / |\boldsymbol{wi}| \times |\boldsymbol{wj}|$ where $|\boldsymbol{wi}|$ and $|\boldsymbol{wj}|$ signify the Euclidean length of the vector $\boldsymbol{wi}$ and sequentially, moreover, the numerator is the dot outcome of $\boldsymbol{wi}$ furthermore $\boldsymbol{wj}$.
Cluster-Width Learning
Given D acquire an informational collection to be clustered, including $NNk(Hi)$ be the method of k-nearest neighbors for the purpose $Hi, clsWidth$ be the method calculating the width (radius) of $NNk(Hi)$ where the width is the measure inside the article Howdy and the most far off item between its colleagues. The expense of k is set to half ×|D| to guarantee a gigantic pack. To find the appropriate worldwide width, we erratically draw two or three articles from $D, H = \{H1; H2; \ldots; Hr) where r \langle |D|$, what's more, for each haphazardly chosen article, the span of its k-nearest neighbors is enlisted, and the ordinary is used as an overall width for D as seeks after:

$$w = \frac{1}{r} \sum_{i=1}^{r} cluWidth\left(NN_K\left(Hi\right), Hi\right)) \tag{3}$$

This procedure segments a data set into various clusters utilizing a huge width to arrange the result of clustering the meagerly distributed items in the n-dimensional range. Be that as it may, enormous clusters from thick territories will be made, for example, clusters C2 and C3. Along these lines, every huge bunch whose size surpasses a client characterized limit (greatest group size) will be separated into various clusters utilizing a width that changes the depth of that collection Akin and Alasalvar (2020). This method progresses continuously the compasses of all clusters are not specifically or comparable to the client characterized limit. The delivered clusters utilizing various-widths clustering web administration suggestion framework, where enormous clusters are parceled into various littler clusters. The primary strides of this technique are condensed in the framework for Coursing in Calculation 1. This method has two elements: Gathering additionally b. The past is a look of class objects, where everything contains characters likewise properties of a gathering. In the fundamental development, the entire enlightening record is perceived as a gathering and it's driven and width is fixed with zeros (Stage 4). The last factor is the division purpose of the best pack's size. At next, the capacity Biggest Group restores the biggest bunch U, which isn't allocated as non-divisional, from Clusters (Sin 14). On the off chance that the size regarding U is more remarkable than (either grows to) b, State (1) implies appropriated to figure a suitable width w for apportioning U. If the estimation of w equivalents zero, U is assigned as non disseminated (Stage 15-20). This occurs because the items in U have similitude's regarding the separation work, and in this manner, they can't be apportioned. Something else, Algorithm 1 is charged into division U (Step 21). On the off chance that the quantity of delivered clusters is only one, the estimation of w is huge and it ought to be limited by 10% and utilized once more (Stage 27). Something else, the new groups conveyed from U is added to Bunches as opposed to U, and the greatest pack again is pulled from Bunches (Stage 22-25). The methods (15-27) are repeated until the partitionable greatest bundle in Groups is less b.

Algorithms

```
   Algorithm 1: Various-Width Clustering
1. Input: Data
2.  Input: α
3.  Output: Clusters
4.  Clusters ← add(Clusters ; Data; zeros; 0);
5.  finished ←0;
6.  while (finished == 0) do
7.  ClsSize ←Clusters :getSize /*
The product of clusters */
8.  Partitioning (Clusters;  α);
9. Merging (Clusters; α );
10.   if |LargestCluster (Clusters)| <= α or
Clusters .getSize==ClsSize then
11.      finished _1
12.     return [Clusters]; end while
13.   Procedure Partitioning (Clusters ; α )
14.     U LargestCluster (Clusters);
15.     while |U:objects| > α do
16.     w using eq.(1);
   17.if(w==0)then
18.   U.nonPartitioned (1);
19.   upgrade (Clusters ; U);
20.   resume;
21.   < tmpClusters > ←Algorithm 1(U,w);
22.   if ClusterNum (tmpClusters) > 1 then
23.    remove(Clusters; U);
24.   attach(Clusters; tmpClusters );
25.    U LargestCluster (Clusters);
26.    else
```

$ww-(w*0:1)$; end while
pass to step 21
Procedure Merging(Clusters; α)
MergingList /* list of *tuples* < */
/* *childClusterID* , *parentClusterID* > */
for each U in Clusters do
j ←using eq. (2) and eq. (3);
/* ID of cluster contained U */
if j not equal 0 then
put < U:getID; j > in *MergingList* ;
while *MergingList* not similar to f produce
for each *tuple* in *MergingList* do
$< i; j >$ ←*tuple* ;
if! *isParent* (*MergingList* ; i) then
MergeClus (Clusters; $i; j$);
delete *tuple* from *MergingList* ;

Algorithm 2: Non-Functional Evaluation
Input: US*u*,1,US*u*,2,⋯,US*u*,***M***; ***Pu***,1,***Pu***,2,⋯,***Pu***,***M***; ***ε***; US1,US2,⋯,US*N*; ***SW***1 , ***SW***2 ,…. . ,SW*N*
Output: ***Uu***, 1, ***Uu***, 2, ⋯, ***Uu***, ***N***
for i=1 to N do
SWi ' = *norm* (***SWi***);
Ssim = ∅;
for j=1 to M do
Si, ***ws*** = ***wsSimWSi*** , , ;
if ***Si***, ***ws***>***εandPu***, ≠ ∅ then
add US***u***, into ***Ssim***;
end if
end for
if <***Num*** then // ***Num*** is a threshold number
Find the top-10 similar users ***Usim*** that have used US***c***,;

$$P_{u,i=}\omega \frac{\sum US_{u,j\in S_{sim}} S_{i,j}^{ws} X P_{uj}}{\sum US_{u,j\in S_{sim}} S_{i,j}^{ws}} + \omega \frac{\sum_{uk \,\epsilon\, U_{sim}} S_{u,uk}^{user} X P_{u,ki}}{\sum_{uk\epsilon\; U\; Sim} S_{u,uk}^{user}}$$

else

$$P_{u,i=}\omega \frac{\sum US_{u,j\in S_{sim}} S_{i,j}^{ws} X P_{uj}}{\sum US_{u,j\in S_{sim}} S_{i,j}^{ws}}$$

end if
Uu, = SW*i* ' × ***Pu***,;
end for
return***Uu***, 1, ***Uu***, 2, ⋯, ***Uu***, ***N***;

Algorithm 3: Web Ser**vic**e Graph Construction

```
Input: S1 H,S2 H,⋯,SNH; S1 P,S2 P,⋯,SNP; Uu,1,Uu,2,⋯,Uu,N;
θH, θP, α, β, γ
Output: Web Service Graph G = (V, E)
V = ∅, E = ∅;
for i=1 to N do
  if SiH ≥ θH or SiP ≥ θP then
    add  to V;
  end if
end for
for each node in V do
  Scoreu, = αSiH +βSiP +γUu,;
end for
for each pair of nodes vi and v in V do
  if (USi, USj) ≥ τ then
    add edge (vi, ei) to E;
  end if
end for
return G = (V, E);
```

An Internet service diagram $G = (V, \mathrm{E})$ is an undirected weighted chart comprising of a lot of nodes V and a lot of edges E, wherein a hub indicates an Internet service competitor, i.e., $vi = \mathrm{US}i$, and an edge signifies that the associated nodes are comparative. $V = K$ is the quantity of nodes (i.e., Web services) that appears in the diagram. Be that as it may, here not all the Internet services in the Internet service pool are utilized for developing the Internet service diagram. Just Internet services with a specific pertinence to client intrigue are utilized.

```
Algorithm 4: Diversified Web Service Ranking
Input: Web Service Graph G = (V, E), parameter λ, adjacency
matrix M
Output: M set a of b ranked Web services
a = ∅;
while |a| ≤ b do
find vmax = arg max v∈ (V−A) (1−λ) Scorev + λb |Nv − (A)|;
  a = a∪ {vmax};
end while
return A;
```

Result and Discussions

To perform reliable examinations, it is perfect to utilize huge scale true Web services. Lamentably, gathering, and getting ready such data is incredibly tedious. Luckily, Zheng et al., 2011 shared an enormous scale genuine Web services dataset gathered throughout their WS-DREAM test. WS-DREAM exists in a Web creeping motor that shakes an openly accessible WSDL document path of the Web. It furthermore assumed non-functional traits (e.g., QoS) of these Web services, which remain considered by 340 appropriated PCs situated in 25 unique nations, from Planet-Lab4

At long last, as a result, we got the top k web administration list which is recommended by the system. Below graphs are showing the excepted practical results for the proposed work clustering-based web service recommendation (CWSR). Figure 2 shows a Comparison of the Precision of Web service Discovery (WSD), CWSR approach, and Figure 3 shows an F-score comparison between existing and proposed systems.

In this test, we execute 100 experiments to evaluate the pick time of our technique. The plans change long; the range in our examination begins with plans comprising of 40 occupations to plans containing 400 employments. Figure 4 demonstrates the determination time came about because of

Figure 2. Measurement of Precision of WSD and CWSR

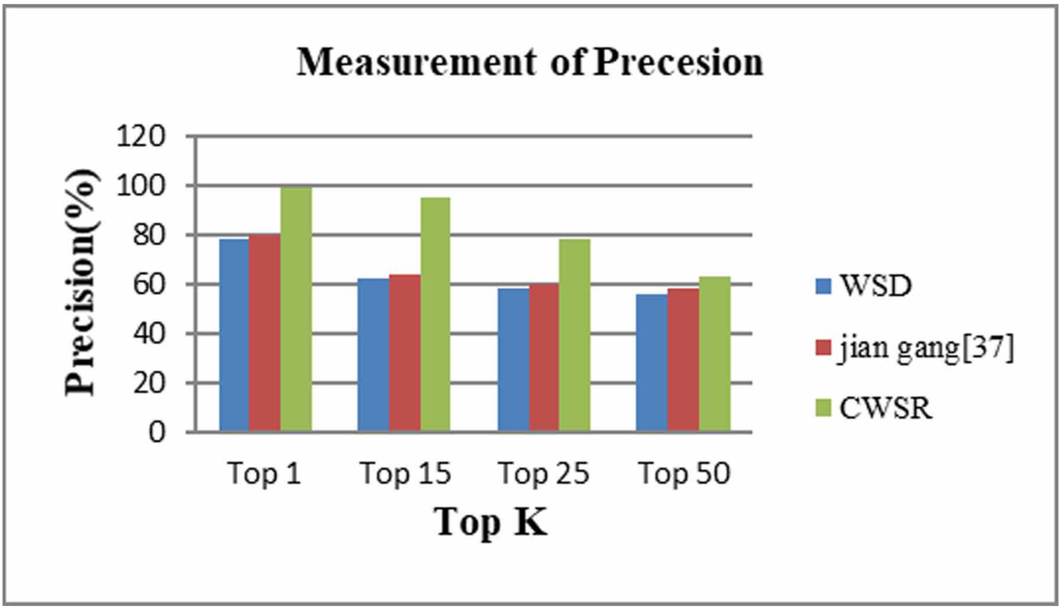
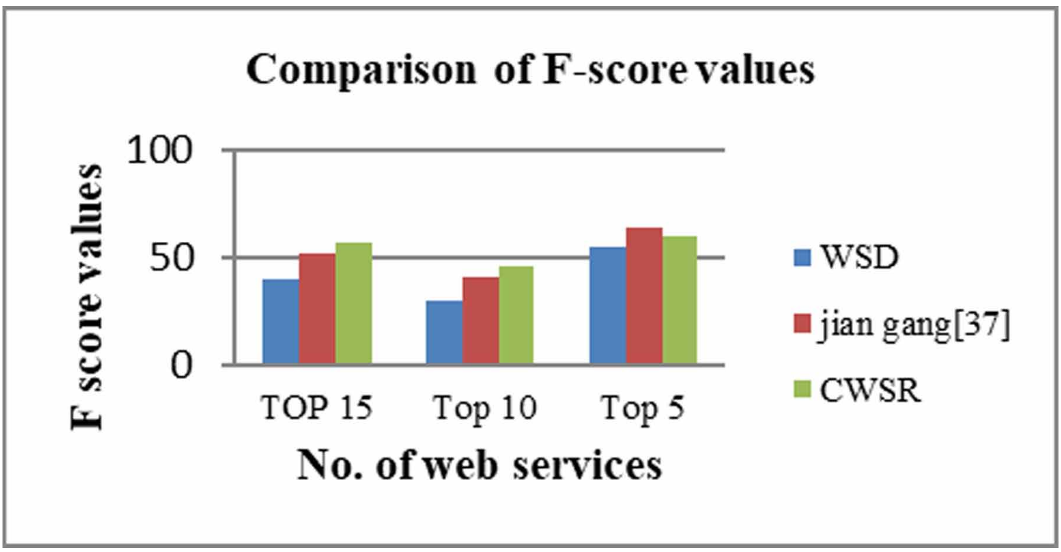


Figure 3. Comparison of F-Score Values for the Proposed System

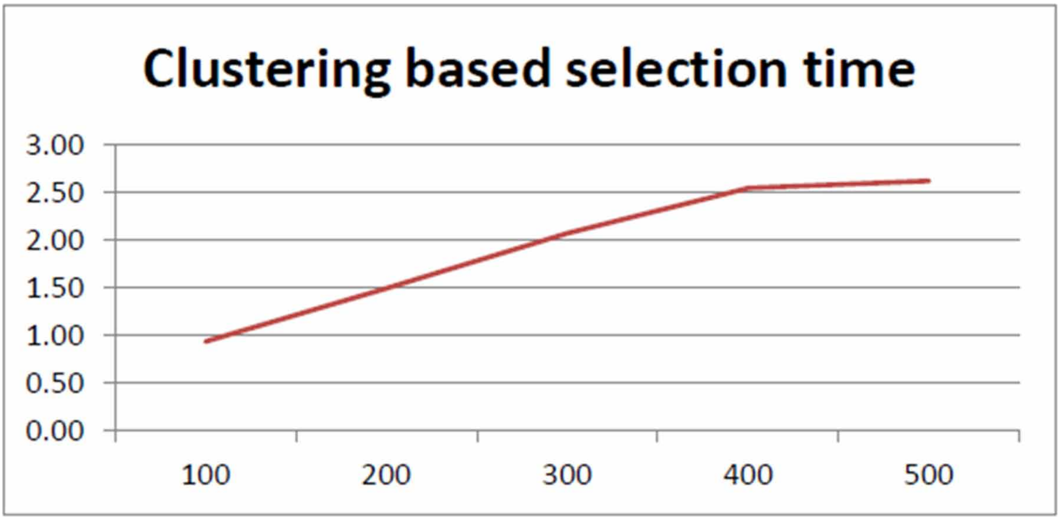


the analysis of the Clustering-based methodology. The time expected to choose web administrations for each activity inside an arrangement is somewhere in the range of 0.8 and 2.7 seconds.

CONCLUSION

This article reviews various recommendation methods to find out the limitations and the problems faced by internet service users while using the services. The work focuses on a cluster-based web service framework for the web service recommendations as to the serving suggestions. The recommendation process uses the similarity measure for the user's requirement. In the web service

Figure 4. Selection Time in Clustering Based Approach



ranking, the score of each node is calculated in the graph. Then the rank will be given to each node in the graph by the score calculated for each node. The node in the graph is the representation of the web service, the client wants to utilize according to his interest. The top k recommendation results are displayed to the user, these are the web service user are willing to access. Our methodology builds the recommendation execution by decreasing the search gap. Moreover, experiment results express that our recommendation strategy operates well and it got greater accuracy than the existing system. In the future, we will think about how to improve our methodology by context information (such as location, time). Likewise, we will investigate different methodologies for QoS expectations.

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Priya Bhaskar Pandharbale received her Master's degree in computers from Pune University in 2013. She has worked in Information Retrieval area for her master's degree. She is a research fellow at Kalinga Institute of Industrial Technology, Bhubaneswar, Orissa, India. She writes and presents widely on Web Service Recommendations.

Sachi Nandan Mohanty (PhD), received Ph.D. from IIT Kharagpur in the year 2015, with MHRD scholarship from Govt of India. He is currently working as an Associate Professor in the Department of Computer Science & Engineering at ICFAI Foundation for Higher Education Hyderabad. Prof. Mohanty research areas include Data mining, Big Data Analysis, Cognitive Science, Emotional Intellegnce, Fuzzy Decision Making, Brain-Computer Interface, and Computational Intelligence. Prof. S N Mohanty has received 3 Best Paper Awards during his Ph.D at IIT Kharagpur from International Conference at Benjing, China, and the other at International Conference on Soft Computing Applications organized by IIT Rookee in the year 2013. He has published 20 SCI Journals. As a Fellow on Indian Society Technical Education (ISTE), The Institute of Engineering and Technology (IET), Computer Society of India (CSI), Senior Member of Institute of Engineers and IEEE Computer Society, he is actively involved in the activities of the Professional Bodies/Societies.

Alok Kumar Jagadev (PhD) is currently working as Professor in the School of Computer Engineering, KIIT Deemed to be University. He has obtained his Master degree from Utkal University in the year 2001 and also obtained Ph.D. degree for his work in the field of Wireless Adhoc Networks from Siksha 'O' Anusandhan University in the year 2011. He has contributed more than 60 papers in various journals and conferences of international repute. He has also contributed three book chapters in international published edited volumes. He has authored/co-authored four textbooks in the field of computer science. He has edited three books for different international publications like IGI Global, Springer etc. He has involved in organizing many international conferences and workshops. He has already supervised more than a dozen of master students and guided five Ph.D. scholars. His research interest includes Soft Computing, Data Mining, Bio-informatics, etc.