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Parameter Reputation Model for Cloud Service Recommendation and Ranking Using Opinion Mining

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ABSTRACT Enabling effective cloud service recommendation and ranking model helps cloud users settle on brief choices when they are up against by an enormous number of choices. This helps to improve the cloud users', as well as the service providers', satisfaction levels. In this paper, parameter reputation-based algorithms are proposed to boost the service selection and ranking. The proposed work employs prominentthe parameters of the Service Measurement Index (SMI) standardized by the Cloud Service Measurement Index Consortium (CSMIC). The parameters are systematically analyzed in order to obtain a user review opinion, such as a positive, negative and neutral view about the parameters. Here, both the positive and negative parameter reputations are addressed. The positive parameter reputation increased the cloud users' choice of service selection and ranking. The negative parameter reputation helped the service providers to realize where they are stand and give them a chance to improve their service provisioning in future endeavors. The detailed experimental results confirm that the proposed models enhance the choice of service selection and ranking.

INDEX TERMS Cloud Computing, Cloud Service Selection, Opinion Mining, Sentiment Analysis, Parameter Reputation.

I. INTRODUCTION

THE tremendous advancement in computer hardware and networking has led to the widespread adoption of information technology (IT) in all domains. The complexities involved in the creation and maintenance of IT infrastructure require a high capital investment, frequent updates and high operation and maintenance costs. It is vital to acquire infrastructure, software and a platform needed to install fully operational IT. The production environment adds more intricate problems. In that front, the high licensing fee and frequent migration to newer versions of software and hardware involve a huge capital investment. In summary, the bane of IT infrastructure management has led to the rise of virtualization and cloud computing. The potential benefits of cloud computing are that the infrastructure/platform/software is offered as a service on demand mode that demonstrates elasticity and is a pay per usage model. The IT infrastructure is not needed to be deployed at the enterprise site. Instead, they are operated, maintained and adopted by the cloud com-puting environment. There is a paradigm shift for all major enterprises, including small and medium enterprises (SMEs) along with individuals moving their IT operations into a cloud computing environment with this perspective [1]. In addition, because of the internet and mobile development, cloud computing has been a significant wave in the IT field. As a result, the major IT players started offering cloud services. Much like any other utility services, the cloud service providers offer their services with various similar features. The cloud users have a wide selection of cloud services, offering a range of providers, and thus, cloud users are face with the issue of choosing the best cloud service for an application. Many researchers contribute their work towards choosing or ranking the cloud services [1-6]. In recent days, cloud user application requirement based the choice of services or ranking service providers based on existing user usage experience and opinion about around

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different cloud service providers. A major portion of these enterprising cloud service providers are also permit the cloud users to register comments and reviews as stated by their utilization experience, similar to a standard E-Commerce sites. However, cloud users cannot evaluate the quality information of all the cloud service providers by utilizing previous client survey remarks to discover the best cloud service provider, because this would be a time consuming and complex process. Moreover, a few quality of service (QoS) parameters are challenging to evaluate. The propose work, with the help of opinion mining techniques, addresses this issue, with the aim of providing a solution. As of late, opinion mining has ascended as one of the popular approach for data recovery and web data examination. These days, it will be thick, as not difficult to express alternately gather opinions regarding a specific product, service or people. Because of the substantial sum for documents it is essential to explore, analyze and organize the content for effective decision making. In this paper, the proposed parameter reputation model addresses service selection issue to analyze sentiments of existing cloud user review comments against different SMI parameters of cloud service providers. The model also addresses the ranking of cloud services based on their parameter significance. In some situation, cloud users' application requirements give more signifi-cance for a particular parameter than some other parame-ters. For instance, the cloud user may require a cost effec-tive cloud service, notwithstanding it is poor in perform-ance and security while another user selecting a cloud service that may give more significance in performance anyway it is high cost. In addition, perspective the pa-rameters importance additionally gives more significance while choosing or ranking cloud services for their specified user requirements. The propose parameter reputation model addresses this issue in order to give importance of the parameters while choosing or ranking cloud services. Usually, the reputation model is used to find the product reputations, such as mobile, camera and others [7,8,9]. The user reviews are used to provide outlines about the parameter reputation of the cloud services along with their aggregate value. The propose parameter reputation model considers SMI metrics coined by CSMIC [10,11]. The SMI is the well known and most commenly used standard to compare cloud services. SMI includes six major groups of attributes, including accountability, agility, financial, performance, assurance and security. Each group includes a set of related subattributes or Key Performance Indicators (KPIs). The rest of this paper is organized as follows: Section 2 describes the works that are closely related and gives the foundation learning for our proposed work; Section 3 presents the different phases of proposed work; Section4 describes the experimental results and the discussion of our proposed work and Section 5 finishes up those pro-posed work and investigates the feasibility of future work.

II. RELATED WORK

This section briefly describes a survey on various cloud service selection approaches ranking the mechanism and application of opinion mining in various scenarios, such as product rating, movie reviews and product reputation. Further, the related work section can be categorized into two sections: (2.1) General cloud service selection and ranking solutions, (2.2) Opinion nining and parameter reputation based solutions. In the following sections, we will confer about survey in each aspect.

A. GENERAL CLOUD SERVICE SELECTION AND RANKING SOLUTIONS

Many researchers proposed various approaches for cloud service selection and ranking. These approaches are mainly considers various QoS parameters and user rating. Garg et al. [1] proposed the Analytical Hierarchical Process (AHP) based Service Measurement Index Cloud (SMI Cloud) framework for ranking cloud services. Their ranking framework assesses those cloud services considering different requisitions that are contingent upon the QoS requirements. It considers all the QoS attributes proposed by the Cloud Service Measurement Index Consortium (CSMIC) [10,11] to compare different cloud services. Their proposed mechanism is likewise tended to the challenge different dimensional units from claiming different QoS attributes by giving a steady best approach to assess the relative ranking of cloud services for each QoS attribute. In addition, Qadir et al. [2] also proposed a framework to measure the quality and pri-orities of cloud services. They proposed an AHP-based ranking mechanism that appraises the cloud services in view of various applications relying upon QoS requirements. Rajasree et al. [5] proposed a trust model for cloud service selection. In their proposed work, an algorithm is defined to ascertain the trust esteem because of the connection between the users and the providers. With the assistance of the ratings given to the cloud service providers by the users, the reliability is assessed by the confidence level, which is controlled by the recent interaction and the interaction intensity. The capability is assessed by parameters, such as security, availability and policies, which are given to the users by the providers. Ding et al. [6] suggested a customized cloud service selection through a multi-attribute trustworthiness evaluation. Their suggested novel service selection ap-proach, for which the missing value prediction and the multi-attribute trustworthiness evaluation need aid, is usually made under record. With the help of collaborative filtering (CF) these predictions focused service selection models produce QoS values or service rankings. Zheng et al. [13] proposed greedy algorithm-based cloud rank approaches to optimally rank the cloud services. Their proposed approaches rank the component rather than the service. However, this algorithm is used to rank a set of items, which treats the unequivocally rated things and the unrated things just as. It does not promise that the explicitly rated items will be ranked effectively. Filali et al. [14] proposed a trust model for cloud service selection.

A trust model expects to provide work with truthful access to users' needs, and it rapidly assesses QoS for cloud services as stated by its effective performance and user ratings, with regard to cloud computing. The enhanced solution is efficient as a result of the convergence speed and stability contrasted with different propositions. Hsu [15] proposed a cloud service selection model (CloudEval) dependent upon a user-specified QoS level. It evaluates the non-functional properties and selects the optimal services that fulfil both a user-specified service level and goals. CloudEval applies a notable multi-attribute decision-making technique, namely a Grey Relational Analysis for the selection process. Preethi et al. [16] proposed a dynamic ranking and selection of cloud services using linear programming. It considers both quantifiable and non-quantifiable QoS parameters to provide an appropriate service that fulfils the greater part of the requirements of cloud service consumers using Linear Programming. In addition, Lie Qu et al. [17] proposed a context-aware and credible cloud service selection model, named CCCloud, that ranks the cloud services based on two types of assessments – 1) subjective assessment extracted from ordinary cloud consumers, and 2) objective assessments from quantitative performance testing parties. The system also proposed a novel approach to examine the credibility and authenticity of cloud users and testing parties. The various experiments proved the outstanding performance of the CCCloud over the existing model, especially in the situation where the performance of the service is incon-sistent, or when some of the reviews are manipulated and diverting. Sun et al. [28] proposed a fuzzy and Choquet integral-based framework called Cloud Service Selection with Criteria Interactions (CSSCI). The framework assesses the impact of various kinds of criteria interactions on cloud service selection results. Furthermore, the priority based CSSCI aims to tackle service selection problems in circumstances where there is an absence of historical information to decide the criteria relations. Zhou et al. [29] exhibited a QoS-based cloud service selection model. In addition, the authors proposed a Chaos Quantum Immune Algorithm (CQIA) to deal with the issue of dodging the downsides, including the selection inefficiency, the algorithm instability and the heavy time overhead. The proposed model uses parallelism and the best part of CQIA algorithm to optimize the cloud service selection. Ding et al. [30] proposed a multi-objective optimization problem for cloud service recommendation, which included a ranking prediction and recommendation algorithms, which at the same time, consider accuracy and diversity. This model improves the cloud user satisfaction in terms of its prediction accuracy and service diversity. In addition, Xiong et al. [31] proposed a past cloud user service usage experience-based approach to predict cloud services by means of Skyline. It eliminates costly and tedious web service invocations. The weak prediction algorithm achieves a better accuracy for ranking prediction. The consequences of these broad analyses demonstrate the adequacy of the proposed methodology. Ibrahim M. Al-Jabri et al. [34] proposed Multi Criteria Decision Making (MCDM) based a group decision-making cloud service selection model. This model involved group of decision makers i.e. 5 decision makers like Chief Executive Of-ficer (CEO), Chief Information Officer (CIO), two Chief Technology Officer (CTO) and Consultant are involved for cloud service selection. Each decision maker, weights of the selection criteria are aggregated, calculated average, standard deviation, coefficient variation of aggregate decision values. Based on deviation of aggregate mean cloud services are ranked and the least coefficient variation of aggregate decision value selected as best cloud service selection. In this system mainly considered seven criteria includes cost, adaptability, availability, urgent needed of service, security, privacy and performance. Ahmed E. Youssef [35] proposed MCDM based novel approach for cloud service selection. This proposed approach with the help of Best Worst Method (BWM) techniques to obtain weights of selection criteria and relative scores of alternatives. The calculated value of BWM then utilized by Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) in order to rank the services. The author also validated and compared using use-case scenario and existing methods. Xuejun Li et al. [36] proposed combinatorial auction based service selection approach for multi-tenant service oriented systems SOSs (CASSMT). This system allows providers to bid services based on quality constraints of SOS. The author measured efficiency of proposed approach based on computation time and different auction rounds in various scenarios on different scales. After analysis of above mentioned studies, we identified some of the limitations. These studies lack in the parameter importance and/or reputation based service selection, comparison and ranking while evaluating objective assessment. In addition, studiesfaliled while evaluating subjective assessment to extract the actual opinion of cloud users about services. Our proposed work addresses these issues. The proposed parameter reputation based algorithms are using existing cloud user reviews and recommend parameter importance based service selection, comparison and ranking.

B. OPINION MINING AND PARAMETERS REPUTATION BASED SOLUTIONS

The opinion mining also called as sentiment analysis is useful techniques to extract the sentiments (positive, negative and neutral) of products and services. Few research studies used this approach for service selection and ranking based on existing user experience views. Yongwen et al. [3] presented an assessment method for parameter importance in the cloud service using a rough set theory. It considers the objective and subjective weight ranking of the attributes for cloud service selection. They proposed a new algorithm for ranking the attributes of cloud services. The datasets, starting with UCI [12] as the training samples, were viewed for the analyses. Wu et al. [4] proposed a reputation revision method for selecting cloud services considering prior knowledge and a market mechanism. Their reputation revision method considers the prior knowledge while calculating the average rating, which encourages the recognition and filtering of out of line evaluations. The overall performance of the proposed system is increased by a market mechanism that permits users and service providers to modify their choice of service and service configuration in a convenient way. Their proposed algorithm clarifies how the business sector exchanges work among purchasers and dealers. The exploratory results demonstrate that the execution extraordinarily enhances the exactness of the reputation revision system. Tian et al. [8] proposed an opinion mining-based product feature taxonomy learning approach, which considers both the features and feature relationships of the product. It builds feature taxonomy, with the aim of utilizing the regular pattern and association rules to profile the product at multiple levels rather than a single level. The proposed approach consists of two main steps, namely, the potential feature generation and the product feature taxonomy construction. The generation of potential product features would, as stated by the outstanding product features, extensively examine the clients' reviews. The product feature taxonomy is constructed with the help of the proposed utilized association rules that are generated from the discovered potential product features. In order to find the missing product features, the authors proposed a feature taxonomy construction algorithm that deals with construction, updating and feature taxonomy expansion. They have executed feature extraction evaluations and structural relations evaluations in order to assess the executions form the recommended approach. Abdel-Hafez et al. [9] presented an opinion mining-based product reputation model to the extract sentiments of the product features. They have considered the text-based user reviews as opposed to the user ratings of the products. The proposed model consists of the feature reputations, the feature impacts and the product reputations. The feature reputations are computed based on the frequencies of the positive and negative opinions of the features and the subfeatures. They also compute the feature impacts in order to give importance to the reputation model. The model provides the weight of every feature and relies on the number of opinions available in the user reviews regarding those features. The final product reputation is the aggregation of the feature reputations are referred from Rongfei [33]. Kumar et al. [18] proposed an opinion mining-based cus-tomer feedback evaluation system. The proposed methodology using ontology toward the feature selection stage will advancement feature-based opinion mining. In addition, its aides to investigate the product worth, performance and opinion from different users based on the individual product features. Furthermore, their proposed score calculation algorithm was used to calculate the score of various features using existing customer opinions. Gurav and Sidnal [19] depicted the strategies utilized for a reputation evaluation of big unstructured data. It also discussed different classifier techniques with a specific end goal of defeating the difficulties and incrementally improving the granularity of opinion catching. Ultimately, they analyzed various techniques and hybrid approaches for an efficient sentiment analysis of big data. Tripathi and Naganna [20] proposed a model for a sentiment analysis of movie reviews that utilized a blend of natural language processing and machine learning approaches. This model analyzed the diverse classification methods in combination with different feature selection schemes. The classification results unmistakably demonstrated that linear SVM provided more precision than Naive Bayes classifier. Additionally, Samsudine al. [21] proposed a feature selection technique in view of an artificial immune system to select the appropriate product features in order to enhance the selection of the product and the feature accuracy, and the author recommended another algorithm known as a Feature Selection based on Immune Network System (FS-INS). The experimental results demonstrated that their recommended algorithm provided a better accuracy over the K-Nearest Neighbor, Naive Bayes and Support Vector Machine. The author of Opinion Mining with Density Forests, Phuc et.al suggests a novel technique to opinion min-ing that makes use of density-based forests. It uses DBSCAN to find clusters of data points in feature vec-tors of hotel and restaurant reviews. These clusters are then used to create random forests that determine whether the opinions given about features in the re-views are good or negative. The suggested ap-proach's usefulness is proved through trials on two typical datasets of hotel and restaurant evaluations in various settings. It is vital to note that classification accuracy varies depending on the individual datasets utilised, review features collected, and density-based forest implementation specifics[40]. The author in another research also stated that in Opinion Mining with Interpretable Random Forests, the authors offer an interpretable random forest model for sentiment analysis on hotel reviews, with the goal of detecting whether the sentiment is fa-vourable or negative. The model also provides criterion-important measure-ments to describe how different parameters such as hotel name, aspect, reviewer, and time influence sen-timent orientation. The model estimates sentiment orientation using an interpretable random forest technique, which was particularly intended for opin-ion mining in hotel reviews. By analysing the inter-pretable random forest on three distinct situations depending on the relevant characteristics, the model shows its ability to identify sentiment orientation on hotel reviews[41]. Mariana et al. proposed that Opinion mining is a kind of Natural Language Processing (NLP) that ex-tracts sentiment analysis from textual data to discover attitudes towards things or people. The project creat-ed an opinion mining system to analyse college learning, employing quantitative descriptive tech-nique and sentiment analysis with Azure machine learn-ing. The sentiment analysis results were favour-able, with a positive class at 0.79 and a neutral class at 0.53. The study indicated that cleaning, labelling, and other categorization methods can help to enhance accuracy. Sentiment analysis with Azure Machine Learning technologies yielded a positive class value of 0.79 and a neutral class value of 0.53. The study found that sentiment analysis was effective in measuring views, emotions, attitudes, and assessments[42]. Severyn et al. [22] characterized a deliberate way to deal with Opinion

Mining on YouTube comments via preparing an arrangement of supervised multi-class classifiers that recognize video and product-related opinions. The fundamental thought of their proposed work was that effective opinion mining can be completed with supervised models trained on high-quality annotations, and it presents a novel annotated corpus of YouTube comments that may offer assistance in the research community and defines novel structural models and kernels for further enhancing feature vectors. Moreover, Kulkarni et al. [23] proposed an opinion mining-based novel way to deal with ranking the product by mining the genuine reviews of the product. Their ranking mechanism likewise provides a strategy to distinguish a fake review given by unknown clients. The product ranking system takes product data in the form of a query, and the system provides the product matching with the customer requirements alongside the product ranking. In addition, Alkalbani et al. [32] investigated the reviews from cloud user experiences with cloud services. The 6000-sample user reviews sentimentally examined and identified the opinions expressed in terms of whether they were positive, negative or neutral. The author also proposed four prediction models to predict the sentiment of user reviews based on existing supervised machine learning algorithms, such as Random Forest, Random Tree, Naive Bayes and K-Nearest Neighbours. Ben-Abdallah et al. [37] presented a system named CROSA that can rank cloud services based on different service-based properties and context of the user. The system considers the online reviews and feedbacks to effectively find the usefulness of the service and to help consumers in the decision-making process. The system used SMI (Service Measurement Index) as a benchmarking instrument for characterizing the key performance indicators (KPIs), such as functional and QoS properties. Here, Functional properties are – RAM, CPU etc, while QoS properties are – availability, security, accountability etc. The use of user context information (like – location, industry type, use-case etc.) along with these properties enhanced the predictive quality of the system. Wenhao Zhang et al. [38] presented a system named 'Weakness Finder' to find the pitfalls and deficiency of the products using user feedback. The system can significantly be useful to help manufacturers improve the quality of their products and thus gaining a competitive advantage. The system is dedicated to using Chinese reviews. The system is able to identify the potential features in the reviews, and then group the features into different pre-defined aspects by using prescribed explicit and implicit grouping methods. The system provided two types of results – 1) It extracted weakness from the target product reviews itself, 2) It extracted weaknesses of the target product by comparing its reviews with the reviews of another competitive product. Yang Liu et al. [39] presented a method based on the sentiment analysis techniques and the intuitionistic fuzzy set theory to rank alternative products through online reviews. The sentiment orientation associated with each product feature is identified using relevant sentiment analysis techniques. Further, the weighted percentages of reviews of one product concerning one feature are calculated using fuzzy set logic and relevant weighting schemes, and according to these weights, an intuitionistic fuzzy number is assigned to each feature that represents the performance of an alternative product concerning a product feature. After analysis of above mentioned work, we find some of the limitations are as follows: (1) limited QoS parameters considered [18,20,32,38,39], (2)parameters importance and/or reputation based evaluation not considered [23,32, 37,38,39], (3) consideration of both positive and negative parameters based comparison lacked [32,37,38,39]. Our proposedmodel addresses all those limitations and provides the efficient service selection and ranking solution. The proposed model considers existing user review comments related to six major groups of SMI parameters and its related KPIs. Furthermore, no study has considered parameter repu-tation based approach. Since cloud computing is a popular business model, considering each parameter reputation and one of the formost in comparing services and rank providers. In addition, no study has considered both positive and negative sentiments in service selection and comparison.

III. PROPOSED SYSTEM

This proposed opinion mining-based parameter reputation model is based on previous user review comments rather than user ratings. A novel method was devised where historical user review comments are sentimentally analysed. We require a comments-based analysis model to analyse the sentiments of the cloud service parameters from the user review comments and provide an opinion about the cloud services. As illustrated in Figure 1, thewhole processof proposed algorithms. The proposed model was designed using the following six phases: i) Data Collection and Pre-processing; ii) Strength of Opinion; iii) Feature Set Construction; iv) Opinion Weight Model; v) Parameter Reputation Model and vi) Cloud Service Ranking. The following section describes, in detail, the working process of the six phases.

Phase 1: Data Collection and Pre-processing The dataset prepare synthetically, since there is no benchmark dataset available for this analysis model. In order to create synthetic dataset partially collect existing cloud user reviews from popular online forums [24,25,26,27]. The collected user reviews of various service providers against the SMI attributes are map into respective parameters in the synthetic dataset. The unavilable reviews are assignes randomly. From the synthesized dataset, each user review comment consider for data pre-processing. The pre-processing step consists of three major processes to pre-process the user reviews. First, the reviews are tokenize, in which the user reviews are broken into a stream of text by phrases, words and symbols. This process explores the prominent words from the reviews that are considered for further processing. Second, using the stop word removal process the unwanted join words, such as 'and', 'are', 'but', 'this' and punctuations. In particular, the tokens are compare with an existing stop word list [28,29]. Third process is the stemming process in order to find the root/base word. This process identifies the exact form of the word by removing the terms ending with 'ing', 'ed', 'ion', 'es' or 'er', by considering the over and under stemming features using existing natural language techniques.

Phase 2: Strength of Opinion In order to assign the opinion of the user review, the root words were matched with existing positive and negative word lists [30,31]. The opinion was assigned based on the occurrence of positive and negative words, i.e., based on the highest number of occurrences. For example, if similar occurrences of both positive and negative words appear in the user review, it would be considered neutral. A neutral opinion reflects the absence of a conclusion about the particular parameter feature and subsequently is not considered in this model. The strength of the opinion S_{ijk} is calculated as given in Eq. 1 and 2, where S_{ijk} represents the strength of the i^{th} cloud service provider, the j^{th} th parameter and the k^{th} th user. Strength of the positive opinion (S_p).

$$S_{ijk} = \frac{\text{pwo}}{\text{pwo} + \text{nwo}} \times 100 \tag{1}$$

The strength of the negative opinion ($S_{ijk} = S_n$) is given by:

$$S_{ijk} = \frac{\text{nwo}}{\text{pwo} + \text{nwo}} \times 100 \tag{2}$$

Key:
1. pwo: Positive Word Occurrences
2. nwo: Negative Word Occurrences

Three levels of opinion strength value were considered for both the positive and negative opinions i.e., $S_{ijk} \in$ {Weak, Moderate, Strong}. Once the strength of the opinion was calculated, a strength value was assigned based on the range of values, which are shown in Table 1. The feature set was formed by grouping the user id, the opinion, the strength of the opinion and the timeline. This is given as the input to the cloud service parameter reputation model algorithm to find the parameter reputation-based opinion.

TABLE 1. Strength Classification

Value	S_{ijk}	S_p	S_n
1	$1 \leq S_{ijk} \leq 34$	Weak	Weak
2	$35 \leq S_{ijk} \leq 69$	Moderate	Moderate
3	$70 \leq S_{ijk} \leq 100$	Strong	Strong

Phase 3: Feature Set of Parameter User Reviews In this phase, construct the feature set in order to define the hierarchy structure of all attributes. This system considers a set of cloud service providers, denoted as $\{CSP_i\}i \rightarrow 1ton$. For each cloud service provider, there are six SMI parameters denoted as $\{P_j\}j \rightarrow 1to6$. Each SMI parameter takes into account 'n' user reviews, denoted as $\{U_k\}i \rightarrow 1ton$.

The user review parameter feature set (f) consists of the following equation.

$$\begin{aligned} f = \{&(U_{ij1}, O_{ij1}, S_{ij1}, T_{ij1}), \\ &(U_{ij2}, O_{ij2}, S_{ij2}, T_{ij2}), \\ &\ldots, (U_{ijn}, O_{ijn}, S_{ijn}, T_{ijn})\}, \quad f \in P_{ij} \end{aligned} \tag{3}$$

In the feature set, U_{ij1} represents the 1st user review of the j-th parameter of the i-th cloud service provider. O_{ij1} represents the opinion of the 1st user review of the j-th parameter of the i-th cloud service provider, where $O_{ij1} \in \{\text{positive, negative, neutral}\}$. S_{ij1} represents the strength of the opinion of the 1st user review of the j-th parameter of the i-th cloud service provider, where $S_{ij1} \in \{\text{weak, moderate, strong}\}$. T_{ij1} represents the user review timestamp of the 1st user review of the j-th parameter of the i-th cloud service provider, where $T_{ij1} \in \{\text{recent, close to recent, past}\}$. The timestamp category of "recent" implies that the reviews were from the last month, and those categorized as "close to recent" include reviews that were 2 to 4 months old. All the other reviews that were older than 4 months were categorized as "Past". This feature set was fed as input to the cloud service parameter reputation model algorithm to find the parameter reputation-based opinion.The pseudo-code for the cloud service recommendation using the parameter reputation model is shown in Algorithm 1.

Phase 4: Opinion Weight Model

From the results of the strength of the positive and negative opinions (S_p and S_n), the opinion weight model was calculated in this phase. The positive opinion weight and the negative opinion weight are calculated using Equations 4 and 5, respectively.

$$\text{WPOS}(P_{ij}) = \frac{\sum_{s_p=1}^{3} NU_{S_p} \times s_p}{TU_{ij} \times M} \times 100 \tag{4}$$

where $\text{WPOS}(P_{ij})$ represents the average weight of all the positive review strength opinions of the i-th cloud service provider and the j-th parameter, which are called recent and close to recent. NU_{S_p} represents the number of users whose positive opinion strength is s_p, and the positive opinion strength s_p is in $\{Weak = 1, Moderate = 2, Strong = 3\}$. TU_{ij} represents the total number of users who gave an opinion for the i-th cloud service provider of the j-th parameter. 'M' represents the maximum strength value of a positive opinion.

$$\text{WNEG}(P_{ij}) = \frac{\sum_{s_n=1}^{3} NU_{S_n} \times s_n}{TU_{ij} \times N} \times 100 \tag{5}$$

Where $\text{WNEG}(P_{ij})$ represents the average weight of all the negative review strength opinions of the $i^{\text{-th}}$ cloud service provider and the $j^{\text{-th}}$ parameter, which were called recent and close to recent. NU_{S_n} represents the number of users whose negative opinion strength is s_n, and the negative opinion strength s_n is in $\{\text{Weak} = 1, \text{Moderate} = 2, \text{Strong} = 3\}$.

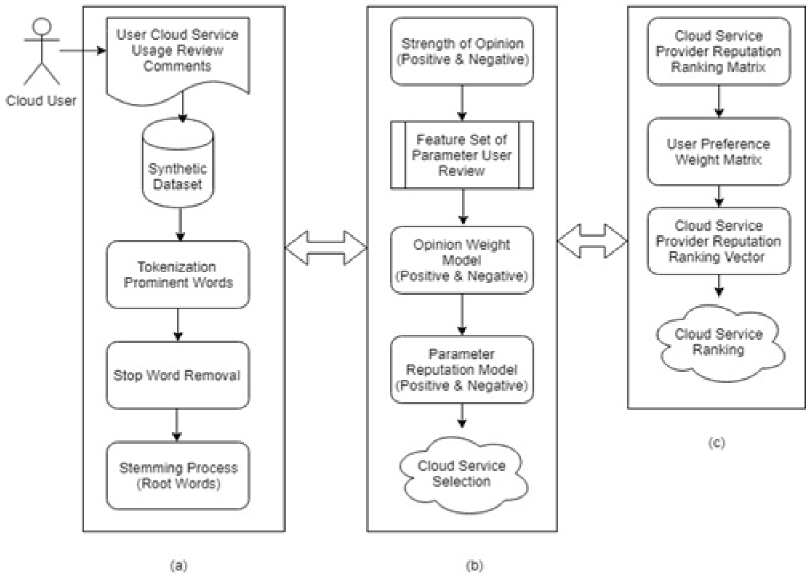

FIGURE 1. System flow chart of the proposed algorithms a) Pre-Processing b) Service Selection c) Service Ranking

TU_{ij} represents the total number of users who gave an opinion for the i-th$^{\text{cloud service provider}}$ of the j-th parameter. 'N' represents the maximum strength value of a negative opinion.

Phase 5: Parameter Reputation Model

After calculating the positive opinion weight and the negative opinion weight, the Positive Parameter Reputation (PPREP) and Negative Parameter Reputation (NPREP) of the i-th$^{\text{cloud service provider}}$ of the j-th parameter are calculated using Equations 6 and 7, respectively.

$$\text{PPREP}_{ij} = \frac{\text{WPOS}(P_{ij})}{\text{WPOS}(P_{ij}) + \text{WNEG}(P_{ij})} \tag{6}$$

$$\text{NPREP}_{ij} = \frac{\text{WNEG}(P_{ij})}{\text{WNEG}(P_{ij}) + \text{WPOS}(P_{ij})} \tag{7}$$

Finally, the Positive Parameter Reputation (PPREP) and the Negative Parameter Reputation (NPREP) of the i-th$^{\text{cloud service provider}}$ under j-th parameter is based on Equation (8).

$$\text{PREP}_{ij} = \begin{cases} \text{PPREP}_{ij}, & \text{if PPREP}_{ij} > \text{NPREP}_{ij} \\ -\text{NPREP}_{ij}, & \text{otherwise} \end{cases} \tag{8}$$

The cloud user may request parameter importance-based cloud services for comparison or ranking rather than cloud services based on general cloud user requirements.

Phase 6: Cloud Service Ranking The final phase deals with ranking the cloud service. The ranking process considers the parameter reputation of all four cloud service providers and the user preference rating of a parameter as an input.

The ranking system aggregated the parameter reputation value of all the parameters for the four service providers in order to find the Cloud Service Provider Reputation Ranking

Algorithm 1 Cloud Service Recommendation

Require: User review feature set f
Ensure: Parameter Reputation of all parameters of all service providers

```
for all i ∈ CSP do
    for all j ∈ CSP_i do
        for all (U_ijk ∩ (O_ijk ∈ pos ∨ O_ijk ∈ neg)) do
            if P_ij ∩ O_ijk ∈ pos then
                Calculate the positive opinion weight: WPOS(P_ij)
            else
                if P_ij ∩ O_ijk ∈ neg then
                    Calculate the negative opinion weight: WNEG(P_ij)
                end if
            end if
        end for
        PPREP_ij = WPOS(P_ij) / (WNEG(P_ij) + WPOS(P_ij))    ▷ Calculate the positive parameter reputation
        NPREP_ij = WNEG(P_ij) / (WNEG(P_ij) + WPOS(P_ij))    ▷ Calculate the negative parameter reputation
        if PPREP_ij ≥ NPREP_ij then
            PREP_ij = PPREP_ij
        else
            PREP_ij = −NPREP_ij
        end if
    end for
end for
```

Algorithm 2 Cloud Service Ranking

Require: Parameter Reputation of the i-th cloud service provider of the j-th parameter
Ensure: Cloud Services Ranking
for all $i \in CSP$ **do**
  for all $j \in \text{CSP}_i$ **do**
    $CSPRRM = \{$aggregate j-th parameter of the i-th cloud service provider parameter reputation $(PREP_{ij})\}$
  end for
end for
// X: Singleton user parameter preference rating matrix of all six SMI parameters
read X
$CSPRRV = (CSPRRM) \times (X)$ ▷ Compute CSPRRV
Sort $CSPRRV$ in ascending order
Rank the Cloud Service

Matrix (CSPRRM). Next, the Cloud Service Provider Reputation Ranking Vector (CSPRRV) is computed with the help of a user parameter preference rating and CSPRRM. Finally, the sorted CSPRRV results help the cloud user to rank the cloud services based on their requirements. Algorithm 3.6.1 describes the process of ranking the best cloud services using the parameter reputation model.

The proposed cloud service ranking model ranks the cloud service using the parameter reputation of each parameter of the four cloud service providers and the cloud user parameter preference rating value. It incorporates the cloud user, as well as a cloud service provider, which will highly satisfy their significant requirements.

IV. RESULTS AND DISCUSSION

The experiment was carried out on the data collected which was performed by two steps are as follows:

1) Review collection from provider forum:
   a) Here, we collect all the reviews of one provider irrespective of parameters
2) Prepare synthetic dataset for further process
   a) Here, prepares dataset to map all the collected reviews into specific parameter and assign manually the unavailable review of specific parameter.

For experiments, we consider totally 300 user reviews of six SIM parameters about 4 cloud service providers. Our synthetic dataset contains totally (300*6*4=7200) reviews. We prepared synthetic datatset due to the unavailability of suitable dataset and importance of the proposed work. The review partially gathered from four popular IaaS public cloud service provider forums, including Amazon, Microsoft Azure, Gogrid and Rackspace [24-27]. The unavailable user reviews of specific parameter are assigned with random textual comments. The experiment has two primary goals. The first one deals with parameter importance-based ranking or a comparison of cloud services with the help of a parameter reputation model. The second primary goal deals with ranking the cloud services based on user preference weights for each SMI parameter using the proposed cloud service ranking model.

The collected data is then preprocessed which in-volves three key steps to refine user reviews. First, reviews are broken down into words and symbols through tokenization to identify important words. Second, unnecessary words like ’and’, ’are’, ‘but’, ’this’, and punctuation are removed using a stop word removal process. Lastly, stemming finds the root/base form of words by removing endings like ’ing’, ’ed’, ’ion’, ’es’, or ’er’, with attention to avoiding both over-stemming and under-stemming through existing natural language techniques.

A. PARAMETERS BASED CLOUD SERVICE RANKING

The proposed model considers SMI metrics coined by CSMIC. SMI includes six major groups of attributes, including accountability, agility, financial, perfor-mance, assurance, and security. Each group includes a set of related sub-attributes or Key Performance Indi-cators (KPIs).

The weighted average model was based on the cloud user review comments in order to find the positive and negative opinion weights for each of the cloud service providers. For instance, Table 2 shows the strength of the opinion and the positive and negative opinion weighted average model of the first cloud service provider. With the help of the positive and negative opinion weight, the positive and negative parameter reputation for the four cloud service providers based on the six SMI parameters was calculated. Table 3 illustrates the overall parameter reputation of the cloud service providers.

TABLE 2. Strength of the Opinion and Opinion Weighted Average Model of the First CSP Parameters

Cloud Service Provider 1	SMI Parameters	Positive Strong Opinion	Positive Moderate Opinion	Positive Weak Opinion	WPOS(P_{ij})	Negative Strong Opinion	Negative Moderate Opinion	Negative Weak Opinion
Accountability	100	60	40	51	50	20	30	24
Agility	91	42	57	46	40	35	35	25
Security	130	95	60	71	5	5	5	15
Performance	97	47	83	52	30	24	19	17
Assurance	98	89	50	58	41	12	10	17
Cost	83	64	63	49	29	12	49	18

The comparison of the parameter reputation against the different SMI parameters for the four cloud service providers is shown in Figure 2. The positive parameter reputation value of the four cloud service providers against the SMI parameters is shown in Table 4. The comparison of the positive parameter reputation against the SMI parameters for a cloud service provider is shown in Figure 3. The

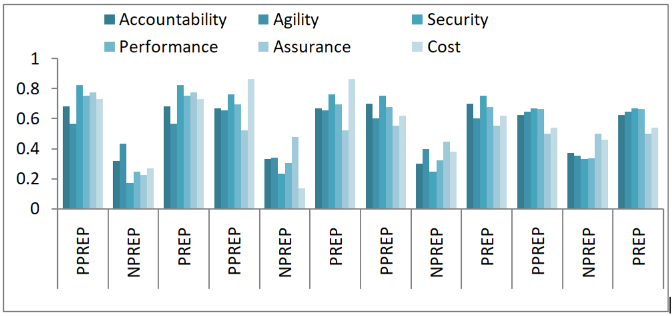

FIGURE 2. Comparison of the Parameter Reputation against the SMI Attributes

negative parameter reputation value of the four cloud service providers against the SMI parameters is shown in Table 5. The comparison of the negative parameter reputation against the SMI parameters for a cloud service provider is shown in Figure 4.

TABLE 3. Overall Parameter Reputation of the Cloud Service Providers (CSP1 and CSP2)

SMI Attributes	CSP1			CSP2		
	PPREP	NPREP	PREP	PPREP	NPREP	PREP
Accountability	0.68	0.320	0.680	0.666	0.333	0.666
Agility	0.567	0.432	0.567	0.657	0.342	0.657
Security	0.825	0.174	0.825	0.763	0.236	0.763
Performance	0.7536	0.246	0.753	0.695	0.304	0.695
Assurance	0.773	0.226	0.773	0.520	0.479	0.520
Cost	0.731	0.268	0.731	0.863	0.136	0.863

TABLE 4. Overall Parameter Reputation of the Cloud Service Providers (CSP3 and CSP4)

SMI Attributes	CSP3			CSP4		
	PPREP	NPREP	PREP	PPREP	NPREP	PREP
Accountability	0.7	0.3	0.7	0.626	0.373	0.626
Agility	0.60	0.397	0.602	0.647	0.352	0.647
Security	0.753	0.246	0.753	0.666	0.333	0.666
Performance	0.676	0.323	0.676	0.662	0.337	0.662
Assurance	0.552	0.447	0.552	0.5	0.5	0.5
Cost	0.618	0.381	0.618	0.540	0.459	0.540

TABLE 5. Positive Parameter Reputation

SMI Attributes	CSP1	CSP2	CSP3	CSP4
Accountability	0.68	0.666667	0.7	0.626667
Agility	0.56716	0.657534	0.60274	0.647887
Security	0.825581	0.763158	0.753247	0.666667
Performance	0.753623	0.695122	0.676923	0.662338
Assurance	0.773333	0.520548	0.552239	0.5
Cost	0.731343	0.863014	0.618421	0.540541

A positive parameter reputation helps the customer to choose a cloud service based on their necessity. A nega-tive parameter reputation provides awareness to the cloud service provider in which they are lacking in, the-reby the cloud

FIGURE 3. Comparison of the Positive Parameter Reputation

TABLE 6. Negative Parameter Reputation

SMI Attributes	CSP1	CSP2	CSP3	CSP4
Accountability	0.32	0.333333	0.3	0.373333
Agility	0.43283	0.342466	0.39726	0.352113
Security	0.174419	0.236842	0.246753	0.333333
Performance	0.246377	0.304878	0.323077	0.337662
Assurance	0.226667	0.479452	0.447761	0.5
Cost	0.268657	0.136986	0.381579	0.459459

FIGURE 4. Comparison of the Negative Parameter Reputation

service provider may be prompted to think about business strategies to improve their customer satisfaction. Figure 5 describes the comparison of each SMI parameter against the four cloud service providers. The figure shows the advantage and disadvantages of the parameters for the four cloud service providers.

The comparative analysis of each parameter justifies the efficiency of the proposed model. According to the observations, the positive and negative reviews are considered for the analysis. The negative parameter reputation helps the cloud service provider analyze the inadequacies in their service provision and also aid them to consider for further improvements in their effective service provision to the cloud user in the near future. The positive parameter reputation allows the cloud user to rank the cloud service based on their parameter preference-based requirements. Figure 6 shows the comparison between the cost and quality performance. This comparison shows which cloud service has the best performance at the minimum cost. Likewise, each parameter can be compared with the other parameters based on the

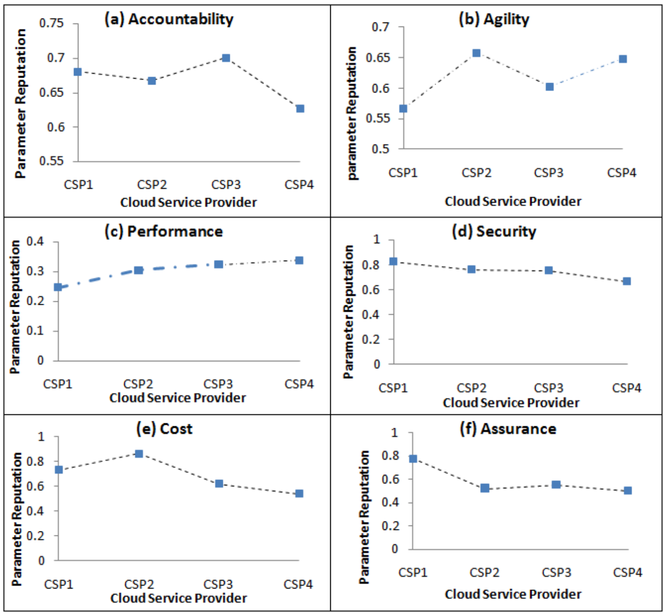

FIGURE 5. Comparisons among the cloud service providers

user requirements to measure the performance. The evaluation and the ranking process for the various cloud service providers enhances the quality of the selection processes in various aspects. The ranking process also identifies the top cloud service providers to highlight the services.

B. USER REQUIREMENT-BASED CLOUD SERVICE RANKING

The ranking computation process considered the user reviews for the four service providers based on the six SMI parameters. The ranking model made use of the parameter reputation value in order to rank the cloud service based on the user parameter preference weights. The parameter reputation value of the four cloud service providers for all six SMI parameters, i.e., Accountability, Agility, Security, Performance, Assurance, and Cost, was as follows:

$$\text{PREP\_Accountability}(0.70000, 0.68000, 0.62667, 0.66667)$$
$$\text{PREP\_Agility}(0.60274, 0.56716, 0.64789, 0.65753)$$
$$\text{PREP\_Security}(0.75325, 0.82558, 0.66667, 0.76316)$$
$$\text{PREP\_Performance}(0.67692, 0.75362, 0.66234, 0.69512)$$
$$\text{PREP\_Assurance}(0.55224, 0.77333, 0.50000, 0.52055)$$
$$\text{PREP\_Cost}(0.61842, 0.73134, 0.54054, 0.86301)$$

Next, the ranking system aggregated all the PREPs of all the parameters to get the Cloud Service Provider Reputation Ranking Matrix (CSPRRM) for the four service providers:

$$\text{CSPRRM} = \begin{bmatrix} 0.70000 & 0.68000 & 0.62667 & 0.66667 \\ 0.60274 & 0.56716 & 0.64789 & 0.65753 \\ 0.75325 & 0.82558 & 0.66667 & 0.76316 \\ 0.67692 & 0.75362 & 0.66234 & 0.69512 \\ 0.55224 & 0.77333 & 0.50000 & 0.52055 \\ 0.61842 & 0.73134 & 0.54054 & 0.86301 \end{bmatrix}^{T}$$

Finally, the Cloud Service Provider Reputation Ranking Vector (CSPRRV) was computed with the help of the CSPRRM and a singleton user parameter preference weight matrix (X) of all six SMI parameters:

$$\text{X} = \begin{bmatrix} 0.3 \\ 0.4 \\ 0.6 \\ 0.8 \\ 0.7 \\ 0.8 \end{bmatrix}$$

$$\text{CSPRRV} = \text{CSPRRM} \times \text{X}$$

The ranking of the cloud services can be chosen based on the resultant CSPRRV:

$$\text{CSPRRV} = \begin{bmatrix} 2.19050 \\ 2.50478 \\ 2.02699 \\ 2.39277 \end{bmatrix}$$

The cloud services are ranked as (CSP2 > CSP4 > CSP1 > CSP3) based on the user requirements.

V. CONCLUSION

In this paper, we proposed parameter reputation model for cloud service recommendation and ranking using sentiment analysis of exiting user reviews rather than overall ratings. It extractes the sentiments from the users reviews and calculate the positive and negative parameter reputations of all six major group of SMI parameters against different service providers. The proposed algorithm holds three major contribu-tions to the cloud environment. Firstly, the positive parameter reputation model gives provison to the cloud user to compare services based on specific parameter feature and also choose the suitable service by considering overall features. Secondly, by utilising the negative parameter reputation is part of this work.It enable the provision to the cloud service provider can identify where they are lacking in contrast with their rivals, and thus, they can enhance their services in near future. Finally, Our proposed system also discusses the cloud service ranking by utilizing parameter repuation. It allows user to rank the cloud service providers according to their QoS requirements. The experimental results clearly showed that our proposed parameter reputation model distinguish featuresto enhance the performance of existing cloud service selection and ranking solutions. In the future work, the parameter reputation model algo-rithm will consider evaluating each possible Key Perfor-mance

Indicators (KPIs) of SMI parameters. This will increase the choice of comparison and ensure effective service selection and ranking. In addition, we will also focus on user emotional based reviews and enhance the performance of the sentiment extraction in cloud service selection and ranking.

The methodology uses opinion mining to tackle unique difficulties in cloud service selection and rank-ing. Obtaining adequate and high-quality data for opinion mining can be difficult, particularly for less popular services; nonetheless, the suggested meth-odology assures that the data acquired is unbiased and reflective of the user base, which is critical for correct suggestions. Also, precisely recognizing and extracting opinions on certain areas is critical for making useful suggestions. The suggested system enhances Aspect-based opinion mining, which adds another degree of complexity to the study. Incorpo-rating varied sources of information such as user pro-files, use trends, and expert views into the suggested recommendation system improves the system's effica-cy and performance.

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