# Exploring Latent Features for Memory-Based QoS Prediction in Cloud Computing

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*Abstract*—With the increasing popularity of cloud computing as a solution for building high-quality applications on distributed components, efficiently evaluating user-side quality of cloud components becomes an urgent and crucial research problem. However, invoking all the available cloud components from user-side for evaluation purpose is expensive and impractical. To address this critical challenge, we propose a neighborhood-based approach, called CloudPred, for collaborative and personalized quality prediction of cloud components. CloudPred is enhanced by feature modeling on both users and components. Our approach CloudPred requires no additional invocation of cloud components on behalf of the cloud application designers. The extensive experimental results show that CloudPred achieves higher QoS prediction accuracy than other competing methods. We also publicly release our large-scale QoS dataset for future related research in cloud computing.

*Keywords*-Cloud Computing; QoS; Prediction;

## I. INTRODUCTION

Cloud computing [1] is Internet-based computing, whereby shared resources, software, and information are provided to computers and other devices on demand. With the exponential growth of cloud computing as a solution for providing flexible computing resources, more and more cloud applications emerge in recent years. The systems architecture of the software systems involved in the delivery of cloud computing (named as cloud applications in this paper), typically involves multiple cloud components communicating with each other over application programming interfaces, usually Web services [2]. How to build high-quality cloud applications becomes an urgent and crucial research problem.

In the cloud environment, designers of cloud applications, denoted as component users, can choose from a broad pool of cloud components when creating cloud applications. These cloud components are usually invoked remotely through communication links. Quality of the cloud applications is greatly influenced by the quality of communication links and the distributed cloud components. To build a high-quality cloud application, non-functional Quality-of-Service (QoS) performance of cloud components becomes an important factor for application designers when making component selection [3]. Moreover, for the existing cloud applications, by replacing low quality components with better ones, the overall quality of cloud applications can be improved.

In recent year, a number of research tasks have been focused on optimal component selection [4], [5] and recommendation [6] in distributed systems or service computing. Typically, evaluations on the component candidates are required to obtain their QoS values. In cloud environment, due to their various locations and communication links, different users will have different QoS experiences when invoking even the same cloud component. Personalized QoS evaluation is required for each user at the user-side. However, a cloud component user in general only invoked a limited number of cloud components in the past and only received QoS performance information of these invoked cloud components. In practice, therefore, conducting real-world evaluations on cloud components to obtain their QoS information from the users' perspective is quite difficult, because:

- Executing invocations for evaluation purposes becomes too expensive, since cloud providers who maintain and host cloud components (e.g., Amazon EC2[1], Amazon S3[2], etc.) may charge for invocations.
- With the growing number of available cloud components over the Internet, it is time-consuming and impractical to conduct QoS evaluations on all accessible cloud components.
- Component users need to focus on building cloud applications on top of various cloud components. While conducting evaluation on a large number of component candidates would introduce extra cost and effort, and sharply slow down the application development progresses.

Based on the above analysis, it is crucial for the cloud platform to deliver a personalized QoS information service

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[1]http://aws.amazon.com/ec2
[2]http://aws.amazon.com/s3

IEEE computer society

to the application designers for cloud component evaluation. In order to provide personalized QoS values on $m$ cloud components for $n$ users by evaluation, at least $n \times m$ invocations need to be executed, which is almost impossible when $n$ and $m$ is very large. However, without sufficient and accurate personalized QoS values of cloud components, it is difficult for the application designers to select optimal cloud component for building high-quality cloud applications. It is an urgent task for the cloud platform providers to develop an efficient and personalized prediction approach for delivering the QoS information service to cloud application designers.

To address this critical challenge, we propose a neighborhood-based approach, called CloudPred, for personalized QoS prediction of cloud components. CloudPred is enhanced by feature modeling on both users and components. The idea of CloudPred is that users sharing similar characteristics (e.g., location, bandwidth, etc.) would receive similar QoS usage experiences on the same component. The QoS value of cloud component $c$ observed by user $u$ can be predicted by exploring the QoS experiences from similar users of $u$. A user is similar to $u$ if they share similar characteristics. The characteristics of different users can be extracted from their QoS experiences on different components by performing non-negative matrix factorization (NMF). By sharing local QoS experience among users, our approach CloudPred can effectively predict the QoS value of a cloud component $c$ even if the current user $u$ has never invoked the component $c$ before. The experimental results show that compared with other well-known collaborative prediction approaches, CloudPred achieves higher QoS prediction accuracy of cloud components. Since CloudPred can precisely characterize users features (will be introduced in Section III-B), even if some users have few local QoS information, CloudPred can still achieve high prediction accuracy.

In summary, this paper makes the following contributions:

1) We formally identify the research problem of QoS value prediction in cloud computing and propose a novel neighborhood-based approach, named Cloud-Pred, for personalized QoS value prediction of cloud components. CloudPred learns the characteristics of users by non-negative matrix factorization (NMF) and explores QoS experiences from similar users to achieve high QoS value prediction accuracy. We consider CloudPred as the first QoS value prediction approach in cloud computing literature.

2) We conduct large-scale experiments to study the prediction accuracy of our CloudPred compared with other approaches. The experimental results show the effectiveness of our approach. Moreover, we also publicly release our large-scale QoS dataset[3] for future research.
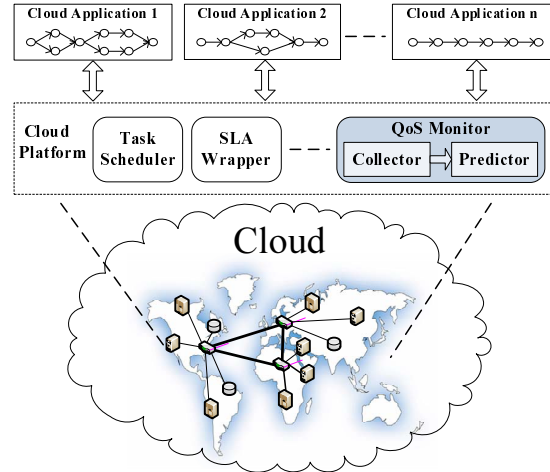
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[3]http://www.wsdream.net



Figure 1.  System Architecture

The remainder of this paper is organized as follows: Section II describes the collaborative QoS framework in cloud environment. Section III presents our CloudPred approach in detail. Section IV introduces the experimental results. Section V discusses related work and Section VI concludes the paper.

## II. COLLABORATIVE FRAMEWORK IN CLOUD

Figure 1 shows the system architecture in cloud computing. In a cloud environment, the cloud provider holds a large number of distributed cloud components (e.g. databases, servers, Web services, etc.), which can be provided to designers for developing various cloud applications. The cloud application designers, called component users in this paper, are located in different geographic and network environments. Since users invoke cloud components via different communication links, their usage experiences on cloud components are diverse in several QoS properties including response-time, throughput, etc. In order to provide personalized quality information of different components to application designers for optimal component selection, personalized QoS value prediction is an essential service of a cloud provider.

Within the cloud platform provided by a cloud provider, there are several modules implemented for managing the cloud components. Examples of management modules include *Task Scheduler*, which is responsible for task scheduling, *SLA Wrapper*, which is responsible for service level negotiation between cloud provider and users, etc. In this paper, we focus on the design of *QoS Monitor*, which is responsible for monitoring the QoS performance of cloud components from the users' perspective. The *QoS Monitor* consists of two sub-units: *Collector*, which is used to collect QoS usage information from various component users, and

*Predictor*, which is supposed to provide personalized QoS value prediction for different component users.

The idea of our approach is to share local cloud component usage experience from different component users, to combine this local information to get a global QoS information of all components, and to make personalized QoS value prediction based on both global and local information. As shown in Figure 1, each component user keeps local records of QoS usage experiences on cloud components. Since cloud applications are running on an identical cloud platform, QoS information can be collected by an identical interface on the platform side. If a component user would like to get personalized QoS information service from the cloud provider, authorization should be given to *Collector* for accessing its local QoS records. *Collector* then collect those local QoS records from different component users. Based on the collected QoS information, *Predictor* can perform personalized QoS value prediction and forward the prediction results to component users for optimizing the design of cloud applications. The detailed collaborative prediction approach will be presented in Section III.

## III. COLLABORATIVE QOS PREDICTION

We first formally describe the QoS value prediction problem on cloud components in Section III-A. Then we learn the user-specific and component-specific features by running latent features learning algorithm in Section III-B. Based on the latent features, similarities between users and components are calculated in Section III-C. Finally, the missing QoS values are predicted by applying the proposed algorithm CloudPred in Section III-D.

### A. Problem Description

Let us first consider a typical toy example in Figure 2(a). In this bipartite graph $G = (U \cup C, E)$, its vertices are divided into two disjoint sets $U$ and $C$ such that each edge in $E$ connects a vertex in $U$ and one in $C$. Let $U = \{u_1, u_2, \cdots, u_4\}$ be the set of component users, $C = \{c_1, c_2, \cdots, c_6\}$ denote the set of cloud components, and $E$ (solid lines) represent the set of invocations between $U$ and $C$. This bipartite graph $G$ is modeled as a weighted directed graph. Given a pair $(i, j)$, $u_i \in U$ and $c_j \in C$, edge $e_{ij}$ is included in $E$ if user $u_i$ has invoked component $c_j$ before. The weight $w_{ij}$ on edge $e_{ij}$ corresponds to the QoS value (e.g., response-time in this example) of that invocation. Given the set $E$, our task is to effectively predict the weight of potential invocations (the broken lines).

The process of cloud component QoS value prediction is illustrated by a user-component matrix as shown in Figure 2(b), in which each entry denotes an observed weight in Figure 2(a). The problem we study in this paper is then how to precisely predict the missing entries in the user-component matrix based on the existing entries. Once the missing entries are accurately predicted, we can provide

users with personalized QoS information, which is valuable for automatic component ranking, component selection, task scheduling, etc.

We observe that although about half of the entries are already known in Figure 2(b), every pair of users still have very few commonly invoked components (e.g., $u_1$ and $u_2$ only invoke $c_1$ in common, $u_3$ and $u_4$ have no commonly invoked components even if together they invoke all the six components). Since the similarity between two users are calculated by comparing their obtained QoS values on common components, the problem of few common components observed above makes it extremely difficult to precisely calculate similarity between users. Motivated by latent factor model [7], we therefore first factorize the sparse user-component matrix and then use $V^T H$ to approximate the original matrix, where the low-dimensional matrix $V$ denotes the user latent feature space, and the low-dimensional matrix $H$ represents the low-dimensional item latent feature space. The rows in $V$ and $H$ represent different features. Each column in $V$ represents an user and each column in $H$ denotes a component. The value of a entry in the matrices indicates how the associated feature applies to the corresponding user or component. In this example we use four dimensions to perform the matrix factorization and obtain:

$$V = \begin{bmatrix} 0.32 & 0.15 & 0.31 & 0.33 \\ 0.23 & 0.15 & 0.26 & 0.28 \\ 0.30 & 0.20 & 0.24 & 0.34 \\ 0.47 & 0.23 & 0.59 & 0.21 \end{bmatrix},$$

$$H = \begin{bmatrix} 0.73 & 0.35 & 0.31 & 0.26 & 0.32 & 0.42 \\ 0.60 & 0.31 & 0.27 & 0.22 & 0.28 & 0.36 \\ 0.69 & 0.37 & 0.32 & 0.27 & 0.33 & 0.45 \\ 0.95 & 0.46 & 0.42 & 0.35 & 0.41 & 0.54 \end{bmatrix},$$

where columns in $V$ and $H$ denote the latent feature vectors of users and components respectively.

Note that $V$ and $H$ are dense matrices with all entries available. Then we calculate the similarity between users and components using 4-dimensional matrices $V$ and $H$ respectively. Therefore, all the missing values can be predicted by employing neighborhood-based collaborative method, as shown in Figure 2(c).

Now we formally define the problem of cloud component QoS value prediction as follows: Given a set of users and a set of components, predict the missing QoS value of components when invoked by users based on existing QoS values. More precisely:

*Let $U$ be the set of $m$ users and $C$ be the set of $n$ components. A QoS element is a triplet $(i, j, q_{ij})$ representing the observed quality of component $c_j$ by user $u_i$, where $i \in \{1, \cdots, m\}$, $j \in \{1, \cdots, n\}$ and $q_{ij} \in \mathbb{R}^k$ is a $k$ dimension vector representing the QoS values of $k^{th}$ criteria. Let $\Omega$ be the set*
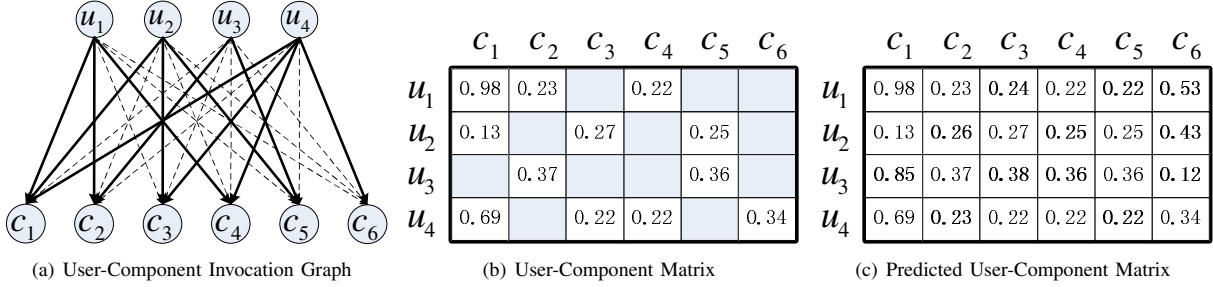
(a) User-Component Invocation Graph

|       | $c_1$ | $c_2$ | $c_3$ | $c_4$ | $c_5$ | $c_6$ |
|-------|-------|-------|-------|-------|-------|-------|
| $u_1$ | 0.98  | 0.23  |       | 0.22  |       |       |
| $u_2$ | 0.13  |       | 0.27  |       | 0.25  |       |
| $u_3$ |       | 0.37  |       |       | 0.36  |       |
| $u_4$ | 0.69  |       | 0.22  | 0.22  |       | 0.34  |

(b) User-Component Matrix

|       | $c_1$ | $c_2$ | $c_3$ | $c_4$ | $c_5$ | $c_6$ |
|-------|-------|-------|-------|-------|-------|-------|
| $u_1$ | 0.98  | 0.23  | 0.24  | 0.22  | 0.22  | 0.53  |
| $u_2$ | 0.13  | 0.26  | 0.27  | 0.25  | 0.25  | 0.43  |
| $u_3$ | 0.85  | 0.37  | 0.38  | 0.36  | 0.36  | 0.12  |
| $u_4$ | 0.69  | 0.23  | 0.22  | 0.22  | 0.22  | 0.34  |

(c) Predicted User-Component Matrix

Figure 2. A Toy Example for QoS Prediction

of all pairs $\{i, j\}$ and $\Lambda$ be the set of all known pairs $(i, j)$ in $\Omega$. Consider a matrix $W \in \mathbb{R}^{m \times n}$ with each entry $w_{ij}$ representing the observed $k^{th}$ criterion value of component $c_j$ by user $u_i$. Then the missing entries $\{w_{ij} | (i, j) \in \Omega - \Lambda\}$ should be predicted based on the existing entries $\{w_{ij} | (i, j) \in \Lambda\}$.

Typically the QoS values can be integers from a given range (e.g. $\{0, 1, 2, 3\}$) or real numbers of a close interval (e.g. $[-20, 20]$). Without loss of generality, we can map the QoS values to the interval $[0, 1]$ using the function $f(x) = (x - w_{min})/(w_{max} - w_{min})$, where $w_{max}$ and $w_{min}$ are the maximum and minimum QoS values respectively.

*B. Latent Features Learning*

In order to learn the features of the users and components, we employ matrix factorization to fit a factor model to the user-component matrix. This method focuses on filtering the user-component QoS value matrix using low-rank approximation. In other words, we factorize the QoS matrix into two low-rank matrices $V$ and $H$. The idea behind the factor model is to derive a high-quality low-dimensional feature representation of users and components based on analyzing the user-component matrix. The premise behind a low-dimensional factor model is that there is only a small number of factors influencing QoS usage experiences, and that a user's QoS usage experience vector is determined by how each factor applies to that user and the items.

Consider the matrix $W \in \mathbb{R}^{m \times n}$ consisting of $m$ users and $n$ components. Let $V \in \mathbb{R}^{l \times m}$ and $H \in \mathbb{R}^{l \times n}$ be the latent user and component feature matrices. Each column in $V$ represents the $l$-dimensional user-specific latent feature vector of a user and each column in $H$ represents the $l$-dimensional component-specific latent feature vector of a component. We employ an approximating matrix $\tilde{W} = V^T H$ to fit the user-item matrix $W$:

$$w_{ij} \approx \tilde{w}_{ij} = \sum_{k=1}^{l} v_{ki} h_{kj}, \qquad (1)$$

The rank $l$ of the factorization is generally chosen so that $(m + n)l < mn$, since $V$ and $H$ are low-rank feature

representations [8]. The product $V^T H$ can be regarded as a compressed form of the data in $W$.

Note that the low-dimensional matrices $V$ and $H$ are unknown and need to be learned from the obtained QoS values in user-component matrix $W$. In order to optimize the matrix factorization, we first construct a cost function to evaluate the quality of approximation. The distance between two non-negative matrices is usually employed to define the cost function. One useful measure of the matrices' distance is the Euclidean distance:

$$F(W, \tilde{W}) = \|W - \tilde{W}\|_F^2 = \sum_{ij} (w_{ij} - \tilde{w}_{ij})^2, \qquad (2)$$

where $\| \cdot \|_F^2$ denotes the Frobenius norm.

In this paper, we conduct matrix factorization as solving an optimization problem by employing the optimized objective function in [8]:

$$\min_{V, H} \quad f(V, H) = \sum_{(i,j) \in \Lambda} [\tilde{w}_{ij} - w_{ij} \log \tilde{w}_{ij}],$$

$$s.t. \quad \tilde{w}_{i,j} = \sum_{k=1}^{l} v_{ki} h_{kj},$$

$$V \geq 0,$$

$$H \geq 0. \qquad (3)$$

where $V, H \geq 0$ is the non-negativity constraints leading to allow only additive combination of features.

In order to minimize the objective function in Eq. (3), we apply incremental gradient descent method to find a local minimum of $f(V, H)$, where one gradient step intends to decrease the square of prediction error of only one rating, that is, $\tilde{w}_{ij} - w_{ij} \log \tilde{w}_{ij}$. We update the $V$ and $H$ in the direction opposite of the gradient in each iteration:

$$v_{ij} = v_{ij} \sum_{k} \frac{w_{ik}}{\tilde{w}_{ik}} h_{jk}, \qquad (4)$$

$$h_{ij} = h_{ij} \sum_{k} \frac{w_{ik}}{\tilde{w}_{ik}} v_{jk}, \qquad (5)$$

$$v_{ij} = \frac{v_{ij}}{\sum_{k} v_{kj}}, \qquad (6)$$

$$h_{ij} = \frac{h_{ij}}{\sum_{k} h_{kj}}. \qquad (7)$$

Algorithm 1 shows the iterative process for latent feature learning. We first initialize matrices $V$ and $H$ with small random non-negative values. Iteration of the above update rules converges to a local minimum of the objective function given in Eq. (3).

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**Algorithm 1**: Latent Features Learning Algorithm

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**Input**: $W, l$
**Output**: $V, H$
1 Initialize $V \in \mathbb{R}^{l \times m}$ and $H \in \mathbb{R}^{l \times n}$ with small random numbers;
2 **repeat**
3    **for** *all* $(i,j) \in \Lambda$ **do**
4       |   $\tilde{w}_{ij} = \sum_k v_{ki} h_{kj}$;
5    **end**
6    **for** *all* $(i,j) \in \Lambda$ **do**
7       |   $v_{ij} \leftarrow v_{ij} \sum_k \frac{w_{ik}}{\tilde{w}_{ik}} h_{jk}$;
8       |   $h_{ij} \leftarrow h_{ij} \sum_k \frac{w_{ik}}{\tilde{w}_{ik}} v_{jk}$;
9       |   $v_{ij} = \frac{v_{ij}}{\sum_k v_{kj}}$;
10     |   $h_{ij} = \frac{h_{ij}}{\sum_k h_{kj}}$;
11    **end**
12    **for** *all* $(i,j) \in \Lambda$ **do**
13     |   $\tilde{w}_{ij} = \sum_k v_{ki} h_{kj}$;
14    **end**
15 **until** *Converge* ;

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### C. Similarity Computation

Given the latent user and component feature matrices $V$ and $H$, we can calculate the neighborhood similarities between different users and components by employing Pearson Correlation Coefficient (PCC) [9]. PCC is widely used in memory-based recommendation systems for similarity computation. Due to the high accuracy, we adopt PCC in this paper for the neighborhood similarity computation on both sets of users and components. The similarity between two users $u_i$ and $u_j$ is defined by performing PCC computation on their $l$-dimensional latent feature vectors $V_i$ and $V_j$ with the following equation:

$$S(u_i, u_j) = \frac{\sum_{k=1}^{l}(v_{ik} - \overline{v}_i)(v_{jk} - \overline{v}_j)}{\sqrt{\sum_{k=1}^{l}(v_{ik} - \overline{v}_i)^2}\sqrt{\sum_{k=1}^{l}(v_{jk} - \overline{v}_j)^2}}, \quad (8)$$

where $v_i = (v_{i1}, v_{i2}, \cdots, v_{il})$ is the latent feature vector of user $u_i$ and $v_{ik}$ is the weight on the $k^{th}$ feature. $\overline{v}_i$ is the average weight on $l$-dimensional latent features for user $u_i$. The similarity between two users $S(i,j)$ falls into the interval $[-1, 1]$, where a larger value indicates higher similarity.

Similar to the user similarity computation, we also employ PCC to compute the similarity between component $c_i$ and item $c_j$ as following:

$$S(c_i, c_j) = \frac{\sum_{k=1}^{l}(h_{ik} - \overline{h}_i)(h_{jk} - \overline{h}_j)}{\sqrt{\sum_{k=1}^{l}(h_{ik} - \overline{h}_i)^2}\sqrt{\sum_{k=1}^{l}(h_{jk} - \overline{h}_j)^2}}, \quad (9)$$

where $h_i = (h_{i1}, h_{i2}, \cdots, h_{il})$ is the latent feature vector of component $c_i$ and $h_{ik}$ is the weights on the $k^{th}$ feature. $\overline{h}_i$ is the average weight on $l$-dimensional latent features for component $c_i$.

### D. Missing QoS Value Prediction

After computing the similarities between users, we can identify similar neighbors to the current user by ordering similarity values. Note that PCC value falls into the interval $[-1, 1]$, where a positive value means similar and a negative value denotes dissimilar. In practice, QoS usage experience of less similar or dissimilar users may greatly decrease the prediction accuracy. In this paper, we exclude those users with negative PCC values from the similar neighbor set and only employ the QoS usage experiences of users with Top-K largest PCC values for predicting QoS value of the current user. We refer to the set of Top-K similar users for user $u_i$ as $\Psi_i$, which is defined as:

$$\Psi_i = \{u_k | S(u_i, u_k) > 0, rank_i(k) \leq K, k \neq i\}, \quad (10)$$

where $rank_i(k)$ is the ranking position of user $u_k$ in the similarity list of user $u_i$, and $K$ denotes the size of set $\Psi_i$.

Similarly, a set of Top-K similar components for component $c_j$ can be denote as $\Phi_j$ by:

$$\Phi_j = \{c_k | S(c_j, c_k) > 0, rank_p(k) \leq K, k \neq j\}, \quad (11)$$

where $rank_j(k)$ is the ranking position of component $c_k$ in the similarity list of component $c_j$, and $K$ denotes the size of set $\Phi_j$.

To predict the missing entry $w_{ij}$ in the user-component matrix, user-based approaches employ the values of entries from Top-K similar users as follows:

$$w_{ij} = \overline{w}_i + \sum_{k \in \Psi_i} \frac{S(u_i, u_k)}{\sum_{a \in \Psi_i} S(u_i, u_a)}(w_{kj} - \overline{w}_k), \quad (12)$$

where $\overline{w}_i$ and $\overline{w}_k$ are the average observed QoS values of different components by users $u_i$ and $u_k$ respectively.

For component-based approaches, entry values of Top-K similar components are employed for predicting the missing entry $w_{ij}$ in the similar way:

$$w_{ij} = \overline{w}_j + \sum_{k \in \Phi_j} \frac{S(i_j, i_k)}{\sum_{a \in \Phi_j} S(i_j, i_a)}(w_{ik} - \overline{w}_k), \quad (13)$$

where $\overline{w}_j$ and $\overline{w}_k$ are the average available QoS values of component $c_j$ and $c_k$ by different users respectively.

In user-component-based approaches, the predicted values in Eq. (12) and Eq. (13) are both employed for more precise prediction in the following equation:

$$w_{ij}^* = \lambda \times w_{ij}^u + (1 - \lambda) \times w_{ij}^c, \quad (14)$$

where $w_{ij}^u$ denotes the predicted value by user-based approach and $w_{ij}^c$ denotes the predicted value by component-based approach. The parameter $\lambda$ controls how much the

hybrid prediction results rely on user-based approach or component-based approach. We summarize the proposed algorithm in Algorithm 2.

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**Algorithm 2**: CloudPred Prediction Algorithm

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**Input**: $W$, $l$, $\lambda$
**Output**: $W^*$
1   Learn $V$ and $H$ by applying Algorithm 1 on $W$;
2   **for** *all* $(u_i, u_j) \in U \times U$ **do**
3     |   calculate the similarity $S(u_i, u_j)$ by Eq. (8);
4   **end**
5   **for** *all* $(c_i, c_j) \in C \times C$ **do**
6     |   calculate the similarity $S(c_i, c_j)$ by Eq. (9);
7   **end**
8   **for** *all* $(i, j) \in \Lambda$ **do**
9     |   construct similar user set $\Psi_i$ by Eq. (10);
10    |   construct similar component set $\Phi_j$ by Eq. (11);
11   **end**
12   **for** *all* $(i, j) \in \Omega - \Lambda$ **do**
13    |   calculate $w_{ij}^u$ by Eq. (12);
14    |   calculate $w_{ij}^i$ by Eq. (13);
15    |   $w_{ij}^* = \lambda \times w_{ij}^u + (1 - \lambda) \times w_{ij}^c$ ;
16   **end**

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## IV. Experiments

In this section, in order to show the prediction quality improvements of our proposed approach, we conduct several experiments to compare our approach with several state-of-the-art collaborative filtering prediction methods.

In the following, Section IV-A gives the description of our experimental dataset, Section IV-B defines the evaluation metrics, Section IV-C compares the prediction quality of our approach with some other methods, and Section IV-D, Section IV-E, and Section IV-F study the impact of training data density, Top-K, and dimensionality, respectively.

### A. Dataset Description

In real world, invoking thousands of commercial cloud components for large-scale experiments is very expensive. In order to evaluate the prediction quality of our proposed approach, we conduct experiments on our Web service QoS dataset [10]. Web service, a kind of cloud component, can be integrated into cloud applications for accessing information or computing service from a remote system. The Web service QoS dataset includes QoS performance of 5,825 openly-accessible real-world Web services from 73 countries. The QoS values are observed by 339 distributed computers located in 30 countries from PlanetLab[4], which is a distributed test-bed consisting of hundreds of computers all over the world. In our experiment, each of the 339 computers keeps invocation records of all the 5,825 Web services by sending null operating requests to capture the characteristics of communication links. Totally 1,974,675 QoS performance
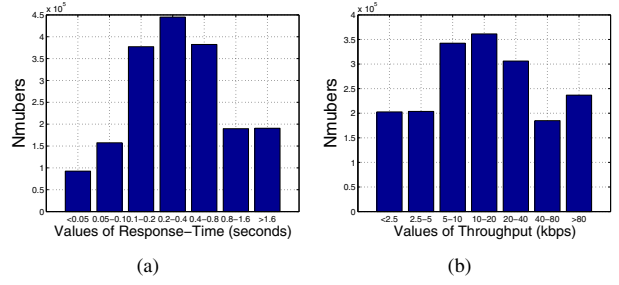
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[4]http://www.planet-lab.org



Figure 3.   Value Distributions

Table I
STATISTICS OF WS QoS DATASET

| Statistics | Response-Time | Throughput |
|---|---|---|
| Scale | 1-20s | 1-1000kbps |
| Mean | 0.910s | 47.386kbps |
| Num. of Users | 339 | 339 |
| Num. of Web Services | 5,825 | 5,825 |
| Num. of Records | 1,974,675 | 1,974,675 |

results are collected. Each invocation record is a $k$ dimension vector representing the QoS values of $k$ criteria. We then extract a set of 339×5825 user-component matrices, each of which stands for a particular QoS property, from the QoS invocation records. For simplicity, we use two matrices, which represent response-time and throughput QoS criteria respectively, for experimental evaluation in this paper. Without loss of generality, our approach can be easily extended to include more QoS criteria.

The statistics of Web service QoS dataset are summarized in Table I. Response-time and throughput are within the range 0-20 seconds and 0-1000 kbps respectively. The means of response-time and throughput are 0.910 seconds and 47.386 kbps respectively. Figure 3 shows the distributions of response-time and throughput. Most of the response-time values are between 0.1-0.8 seconds and most of the throughput values are between 5-40 kbps.

### B. Metrics

We assess the prediction quality of our proposed approach in comparison with other methods by computing Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The metric MAE is defined as:

$$MAE = \frac{\sum_{i,j} |w_{ij} - w_{ij}^*|}{N}, \qquad (15)$$

and RMSE is defined as:

$$RMSE = \sqrt{\frac{\sum_{i,j}(w_{ij} - w_{ij}^*)^2}{N}}, \qquad (16)$$

where $w_{ij}$ is the QoS value of Web service $c_j$ observed by user $u_i$, $w_{ij}^*$ denotes the QoS value of Web service $c_j$ would be observed by user $u_i$ as predicted by a method, and $N$ is the number of predicted QoS values.

## C. Performance Comparison

In this section, we compare the prediction accuracy of our proposed approach CloudPred with some state-of-the-art approaches:

1) UPCC (User-based collaborative filtering method using Pearson Correlation Coefficient): this method employs PCC to calculate similarities between users and predicts QoS value based on similar users [11], [12].
2) IPCC (Item-based collaborative filtering method using Pearson Correlation Coefficient): this method employs PCC to calculate similarities between Web services and predicts QoS value based on similar items (item refers to component in this paper) [9].
3) UIPCC (User-item-based collaborative filtering method using Pearson Correlation Coefficient): this method is proposed by Ma et al. in [13]. It combines UPCC and IPCC approaches and predicts QoS value based on both similar users and similar Web services.
4) NMF (Non-negative Matrix Factorization): This method is proposed by Lee and Seung in [8]. It applies non-negative matrix factorization on user-item matrix for missing value prediction.

In this paper, in order to evaluate the performance of different approaches in reality, we randomly remove some entries from the matrices and compare the values predicted by a method with the original ones. The matrices with missing values are in different sparsity. For example, 10% means that we randomly remove 90% entries from the original matrix and use the remaining 10% entries to predict the removed entries. The prediction accuracy is evaluated using Eq.(15) and Eq.(16) by comparing the original value and the predicted value of each removed entry. Our proposed approach CloudPred performs matrix factorization in Section III-B and employs both similar users and similar Web services for predicting the removed entries. The parameter settings of our approach CloudPred are Top-K=10, dimensionality=20, $\lambda = 0.5$ in the experiments. Detailed impact of parameters will be studied in Section IV-D, Section IV-E and Section IV-F.

The experimental results are shown in Table II. For each row in the table, we highlight the best performer among all methods. From Table II, we can observe that our approach CloudPred obtains better prediction accuracy (smaller MAE and RMSE values) than other methods for both response-time and throughput under different matrix densities. The MAE and RMSE values of dense matrices (e.g., matrix density is 80% or 90%) are smaller than those of sparse matrices (e.g., matrix density is 10% or 20%), since a denser matrix provides more information for predicting the missing values. In general, the MAE and RMSE values of throughput are larger than those of response-time because the scale of throughput is 0-1000 kbps, while the scale of response-time is 0-20 seconds. Compared with other methods, the improvements of our approach CloudPred are significant, which demonstrates that the idea of combining global and local information for QoS prediction is realistic and reasonable.

## D. Impact of Matrix Density

In Figure 4, we compare the prediction accuracy of all the methods under different matrix densities. We change the matrix density from 10% to 90% with a step value of 10%. The parameter settings in this experiment are Top-K=10, dimensionality=20, and $\lambda = 0.5$.

Figure 4(a) and Figure 4(b) show the experimental results of response-time, while Figure 4(c) and Figure 4(d) show the experimental results of throughput. The experimental results show that our approach CloudPred achieves higher prediction accuracy than other competing methods under different matrix density. In general, when the matrix density is increased from 10% to 30%, the prediction accuracy of our approach CloudPred is significantly enhanced. When the matrix density is further increased from 30% to 90%, the enhancement of prediction accuracy is quite limited. This observation indicates that when the matrix is very sparse, collecting more QoS information will greatly enhance the prediction accuracy, which further demonstrates that sharing local QoS information among cloud component users could effectively provide personalized QoS estimation.

In the experimental results, we observe that the performance of IPCC is much worse than that of other methods. The reason is that in our Web service dataset the number of users, which is 339, is much smaller than the number of components, which is 5258. When some entries are removed from the user-component matrices, the number of common users between two components, on average, are very small, which would greatly impact the accuracy of common user based similarity computation between components. Therefore, the prediction accuracy of similar items based method IPCC is greatly decreased by the inaccuracy similarity computation between components.

## E. Impact of Top-K

The parameter Top-K determines the size of similar user and similar component sets. In Figure 5, we study the impact of parameter Top-K by varying the values of Top-K from 10 to 50 with a step value of 10. Other parameter settings are dimensionality=10 and $\lambda = 0.5$.

Figure 5(a) and Figure 5(b) show the MAE and RMSE results of response-time respectively, while Figure 5(c) and Figure 5(d) show the MAE and RMSE results of throughput respectively. The experimental results show that our approach CloudPred achieves best prediction accuracy(smallest MAE and RMSE values) when Top-K is set around 10. Under both sparse matrix, whose density is 10%, and dense matrix, whose density is 90%, all the prediction accuracies decreases when we decrease the Top-K value from 10 to 2

| Matrix Density | Metrics | Response-Time (seconds) | | | | | Throughput (kbps) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | IPCC | UPCC | UIPCC | NMF | CloudPred | IPCC | UPCC | UIPCC | NMF | CloudPred |
| 10% | MAE | 0.7596 | 0.5655 | 0.5654 | 0.6754 | **0.5306** | 31.6722 | 26.2015 | 22.6567 | 19.7700 | **19.0009** |
| | RMSE | 1.6133 | 1.3326 | 1.3309 | 1.5354 | **1.2904** | 65.5220 | 61.9658 | 57.4653 | 57.3767 | **51.8236** |
| 20% | MAE | 0.7624 | 0.5516 | 0.5053 | 0.6771 | **0.4745** | 35.1780 | 21.9313 | 18.1230 | 15.7794 | **15.4203** |
| | RMSE | 1.6257 | 1.3114 | 1.2486 | 1.5241 | **1.1973** | 66.6028 | 56.5441 | 50.0435 | 50.1402 | **44.8975** |
| 80% | MAE | 0.6703 | 0.4442 | 0.3873 | 0.3740 | **0.3704** | 29.9146 | 14.5497 | 12.4880 | 12.5107 | **10.7881** |
| | RMSE | 1.4102 | 1.1514 | 1.0785 | 1.1242 | **1.0597** | 64.3079 | 44.3738 | 39.6017 | 39.2029 | **36.8506** |
| 90% | MAE | 0.6687 | 0.4331 | 0.3793 | 0.3649 | **0.3638** | 29.9404 | 13.8761 | 12.0662 | 11.6960 | **10.4722** |
| | RMSE | 1.4173 | 1.1264 | 1.0592 | 1.1121 | **1.0359** | 63.7149 | 42.5534 | 38.0763 | 36.7555 | **35.9225** |
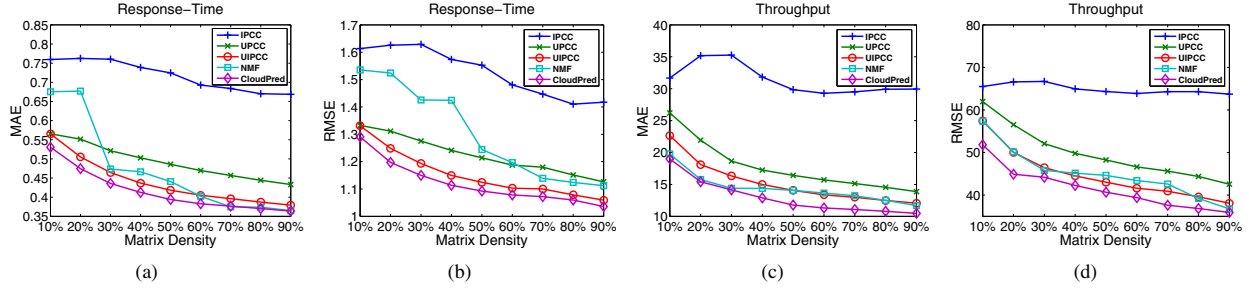


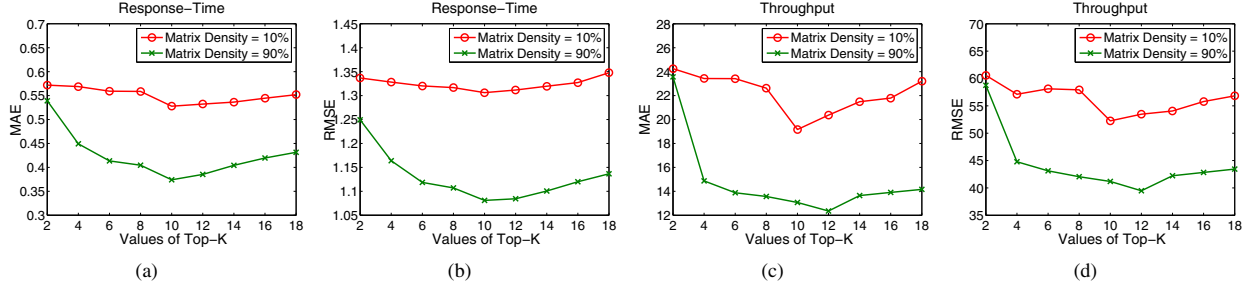Figure 4. Impact of Matrix Density



Figure 5. Impact of Top-K

or increase from 10 to 18. This is because too small Top-K value will exclude useful information from some similar users and similar components, while too large Top-K value will introduce noise from dissimilar users and dissimilar components, which will impact the prediction accuracy.

*F. Impact of Dimensionality*

The parameter dimensionality determines the number of latent features used to characterize user and cloud component. In Figure 6, we study the impact of parameter dimensionality by varying the values of dimensionality from 10 to 50 with a step value of 10. Other parameter settings are Top-K=10, and $\lambda = 0.5$.

Figure 6(e) and Figure 6(f) show the MAE and RMSE values of response-time, while Figure 6(g) and Figure 6(h) show the MAE and RMSE values of throughput. When the matrix density is 90%, we observe that our approach CloudPred achieves the best performance when the value

of dimensionality is 30, while smaller values like 10 or larger values like 50 can potentially hurt the prediction accuracy. This observation indicates that when the user-component matrices are dense, 10 latent factors are not enough to characterize the features of user and component which are mined from the rich QoS information, while 50 latent factors are too many since it will cause overfitting problem. When the matrix density is 10%, we observed that the prediction accuracy of our approach CloudPred decreases (MAE and RMSE increase) when the value of dimensionality is increased from 10 to 50. This observation indicates that when the user-component matrices are sparse, 10 latent factors are already enough to characterize the features of user and component which are mined from the limited user-component QoS information, while other larger values of dimensionality will cause the overfitting problem.
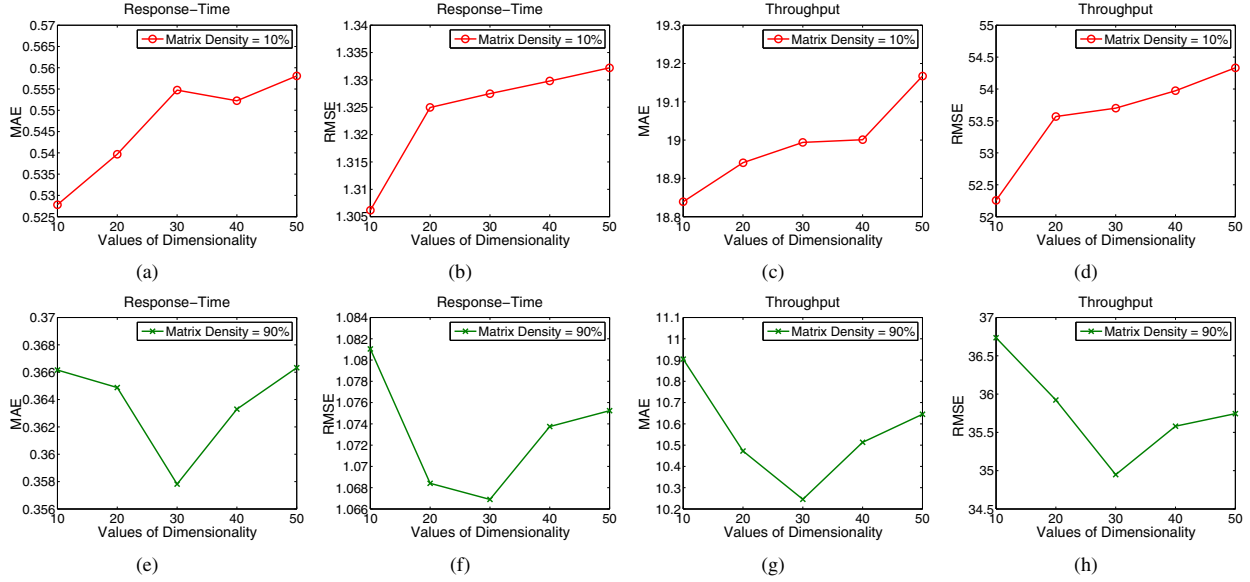
Figure 6. Impact of Dimensionality

## V. RELATED WORK

Cloud computing [1] has been in spotlight recently. A number of investigations have been carried out focusing on different kinds of research issues such as fault tolerance [14], resiliency quantification [15], component ranking [6], resource consistency [16], etc. Quality-of-Service (QoS) has been widely employed as a quality measure for evaluating non-functional features of software systems and components [4], [17], [18]. QoS performance of cloud components can be measured either from the component provider's perspective or from the user's observation. QoS values measured at the component provider side (e.g. price, availability, etc.) are usually identical for different users, while QoS values observed by different users may vary significantly due to the unpredictable communication links and heterogeneous user environments. Based on the QoS performance of components, several approaches have been proposed to optimize web component selection [4], [5], [19] in improving the whole quality of web application.

The above approaches usually assume that the QoS values are already known, while in reality a user cannot exhaustively invoke all the components in cloud. In this paper, we focus on predicting missing QoS values by collaborative filtering approach to enable the optimal cloud component selection.

Collaborative filtering approaches are widely adopted in commercial recommender systems [9], [13], [20]. The neighborhood-based (memory-based) approaches are one of the most popular prediction methods in collaborative filtering systems. The most analyzed examples of neighborhood-based collaborative filtering include user-based approaches [11], item-based approaches [21], [22], [23], and their fusion [13]. These approaches employ similarity computation to find similar users and items in making the QoS value prediction. VSS algorithm [11] and PCC algorithm [9] are often employed as the similarity computation methods. Compared with VCC-based approaches, PCC-based approaches usually achieve higher prediction accuracy due to the consideration on difference between users' rating styles.

In addition to memory-based methods, model-based approaches, which employ machine learning techniques to train a predefined model from the training datasets, are also widely studied. Model-based approaches include several types: the clustering models [24], the latent factor models [7], the aspect models [25], etc. Lee et al. [8] presented an algorithm for non-negative matrix factorization that is able to learn the parts of facial images and semantic features of text. The premise behind a low-dimensional factor model is that there is only a small number of factors influencing the QoS values in the user-component matrix, and that a user's factor vector is determined by how much each factor applies to that user. Compared with other methods, such as vector quantization which learns holistic representations, non-negative matrix factorization method proposed in [8] learns parts-based representations by using non-negativity constraints, which allow only additive combinations.

The memory-based approaches employ the information from similar users and items (local information) for predicting missing values, while the model-based approaches adopt information from the whole user-item matrix for making value prediction. In this paper, we take advantage of both types of approaches for predicting missing QoS values.

By exploring global information using NMF technique and adopting local information from similar users and items simultaneously, CloudPred achieves higher accuracy when predicting missing QoS values.

## VI. CONCLUSION AND FUTURE WORK

Based on the intuition that a user's cloud component QoS usage experiences can be predicted by exploring the past usage experience from both the user and its similar users, we propose a novel neighborhood-based approach, which is enhanced by feature modeling on both user and component, called CloudPred, for collaborative and personalized QoS value prediction on cloud components. Requiring no additional invocation of cloud components, CloudPred makes the QoS value prediction by taking advantage of both local usage information from similar users and similar components and global invocation information shared by all the users. The extensive experimental results show that our approach CloudPred achieves higher prediction accuracy than other competing methods.

Since the Internet environment is highly dynamic, the QoS performances of a cloud component may be variable against time (e.g., due to the network traffic, server workload, etc.). In our current approach, the QoS values are observed over a long period, which represent the average QoS performance of cloud components. Since the average QoS performance of cloud components is relatively stable, the predicted QoS values provide valuable information of unused cloud components for the users. In our future work, we will explore an online prediction algorithm to handle the dynamically changing QoS values by fusing with the time information.

Currently, we are collecting QoS information of Web service, which is a kind of cloud component. In the future, we will conduct more experiments to evaluate our approach in commercial clouds which contain multiple kinds of cloud components. For future work, we will investigate more techniques for improving the similarity computation (e.g., clustering models, latent factor models, data smoothing, etc.). We will also conduct more investigations on the correlations and combinations of different QoS properties.

## ACKNOWLEDGMENT

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