QoS Prediction for Web Services via $L_{2,1}$-Norm Regularized Matrix Completion Approach

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***Abstract*—In this paper, by introducing the $\ell_{2,1}$ -norm regularization factor into the conventional matrix completion approach, an efficient QoS prediction approach named $\ell_{2,1}$ -norm regularized matrix completion (NRMC) is proposed to support the QoS-based web service selection. The NRMC can predict the missing QoS values and simultaneously correct the corrupted ones from a set of sparsely collected training samples with structured noise. Experimental results performed on a real dataset demonstrate the feasibility of our proposed approach.**

***Index Terms*—Web service, QoS prediction, matrix completion, $\ell_{2,1}$ -norm regularization.**

I. Introduction

With the exponential growth of alternative web services that provide the same functionality, Quality-of-Service (QoS) is becoming important for describing nonfunctional properties of web services. In recent years, there are a number of papers about QoS-based web service selection, which common premise is that the whole QoS values of candidate services are known. However, this premise may not be true. Currently, the main approach for obtaining QoS values is web service evaluation, while conducting web service evaluation is time-consuming and resource-consuming. Therefore, a user can hardly have invoked all services, which mean the QoS values of services that the user has not invoked are unknown. To predict those missing QoS values, some approaches have been proposed, including User-based Pearson Correlation Coefficient (UPCC) approach [1] and Neighborhood Integrated Matrix Factorization (NIMF) approach [2], etc. However, all these methods assume that the collected QoS values used as training samples are accurate. When the sampled QoS values are corrupted with noise, the existing QoS prediction approaches will obtain a degenerative performance. In real applications, there usually exist few dishonest QoS providers who could submit some fake or corrupted QoS values to attract interested user or malign a competitor's service. In order to address this problem, we employ the $\ell_{2,1}$ -norm regularization factor to modify the conventional matrix completion (MatC) [3] approach, and propose a $\ell_{2,1}$ -norm regularized matrix completion (NRMC) approach to predict the missing QoS values and simultaneously correct the corrupted ones from a set of sparsely collected training samples with structured noise.

II. The Proposed $\ell_{2,1}$ -Norm Regularized Matrix Completion Appraoch

Given m users and n web services, this will yield a $m \times n$ sampled QoS matrix R with users as rows and services as columns, in which entry r_{ij} denote the QoS value (e.g. response-time or throughput) of web service j observed by user i. If the entry r_{ij} is unavailable, then $r_{ij} = null$, denoting that web service j has never been invoked by user i before.

According to the reference [3], the conventional matrix completion (MatC) problem can be written as

$$\min_{X,Z} \|X\|_* \qquad s.t.\ \mathrm{P}_\Omega(M) = \mathrm{P}_\Omega(X+Z) \tag{1}$$

where M is a $m \times n$ sampled matrix, X is a variable matrix, Z is a noise matrix, Ω is a subset of index pairs (i, j). $\mathrm{P}_\Omega(\cdot)$ is the projector operator, and the nuclear-norm $\|X\|_*$ is the summation of all the singular values. Obviously, the QoS prediction problem can be naturally cast as a matrix completion problem. Since most users invoke only a small portion of the services, we typically only know a small subset $\left\{ r_{ij} \middle| (i,j) \in \Omega \right\}$ of the QoS entries. Based on the known QoS values, we want to predict those missing QoS values.

Since the sampled QoS matrix is usually corrupted by the row structured noise, we can formulate our problem as follows:

$$\min_{X,Z} \|X\|_* + \lambda \|Z\|_{2,1} \qquad s.t.\ \mathrm{P}_\Omega(R) = \mathrm{P}_\Omega(X+Z) \tag{2}$$

where $\|Z\|_{2,1}$ is employed to smooth the row structured noise, and defined as $\|Z\|_{2,1} = \sum_{i=1}^{m} (\sum_{j=1}^{n} Z_{ij}^2)^{1/2}$, and λ is a tunable parameter which tunes the degree of row structured noise and the goal of achieving low rank.

In order to efficiently solve the problem (2), inspired from the idea of Singular Value Threshold (SVT) algorithm [4], we furthermore relax the problem (2) as the following proximal problem:

$$\min_{X,Z} \tau(\|X\|_* + \lambda \|Z\|_{2,1}) + 1/2 \|X\|_F^2 \ \ st.\ \mathrm{P}_\Omega(R) = \mathrm{P}_\Omega(X+Z) \tag{3}$$

where τ is a large positive scalar so that the objective function is only perturbed slightly. By introducing a Lagrange multiplier Y to remove the equality constraint, one has the Lagrangian function of problem (3):

$$L(X,Z,Y) = \|X\|_* + \lambda\|Z\|_{2,1} + 1/(2\tau)\|X\|_F^2 + 1/\tau\langle Y, \mathrm{P}_\Omega(R-X-Z)\rangle$$
$$= \|X\|_* + \lambda\|Z\|_{2,1} + 1/(2\tau)\|X\|_F^2 + 1/\tau\langle \mathrm{P}_\Omega(Y), R-X-Z\rangle$$
$$= \|X\|_* + \frac{1}{2\tau}\|X - \mathrm{P}_\Omega(Y)\|_F^2 + \lambda\|Z\|_{2,1} + \frac{1}{\tau}\langle \mathrm{P}_\Omega(Y), R-Z\rangle - \frac{1}{2\tau}\|\mathrm{P}_\Omega(Y)\|_F^2$$

For convenience, we introduce the soft-thresholding shrinkage operator $S_\tau(x) = \mathrm{sgn}(x)\max(|x|-\tau, 0)$, where $x \in R$ and $\tau > 0$, this operator can be extended to vectors and matrices by applying it element-wise. Algorithm 1 describes the tractable solution about the problem (3).

Algorithm 1: The NRMC algorithm

Input: Sampled set Ω and sampled entries $\mathrm{P}_\Omega(R)$, parameter λ and τ.

Output: X^{opt}.

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initialize k=1, Z_0 = I, Y_0 = 0, σ = 1.5, where I is an identity matrix;
while not converged do
    (U, Σ, V) = svd(P_Ω(Y_{k-1}));
    X_k = U S_τ(Σ) V^T;
    Y_k = Y_{k-1} + σ P_Ω(R - X_k - Z_{k-1});
    initialize t=1, D^0 = I;
    while not converged do
        Z_k^t = (1/(2λτ)) (D^{t-1})^{-1} P_Ω(Y_k);
        D^t = diag(d_ii^t),   where d_ii^t = 1/(2||(Z_k^t)^(i)||_2 + ξ),
        (Z_k^t)^(i) is the i-th row of matrix Z_k^t, ξ is a very
        small positive scalar, usually eps;
        t=t+1;
    end while
    k=k+1;
end while;
```

III. Performance Evaluation

We have conducted some experiments using a real public web services QoS dataset, which is collected by Zibin Zheng *et.al.*(http://www.wsdream.net). It contains two 339×5825 matrices for response-time and throughput. In our experiments, *NMAE* (Normalized Mean Absolute Error) is used to evaluate the prediction accuracy. The *NMAE* is defined as:

$$NMAE = \left(\sum_{ij}\left|r_{ij} - \widetilde{r_{ij}}\right| / N\right) \Big/ \sum_{ij}\widetilde{r_{ij}} / N \qquad (4)$$

where r_{ij} denotes the predicted QoS value of service j observed by user i, $\widetilde{r_{ij}}$ stands for the real QoS value, and N is the total number of predicted QoS values. A smaller *NMAE* value means a better prediction performance.

We compare our approach with well-known UPCC, NIMF and MatC. In order to conduct our experiments realistically, we first randomly select 5% rows of the whole QoS matrix to add uniform random noise, and then remove some entries from the corrupted matrices with different density (i.e. 5% and 10%). Matrix density 10% means that we randomly select 10% entries to predict the remaining 90% entries. The experimental results are shown in Table 1. From Table 1, we can see that our proposed NRMC approach obtains smaller *NMAE* values, which means higher prediction accuracy. Table 1 still shows that the *NMAE* value of each approach becomes smaller with the increase of the sampled matrix size (from 5% to 10%), indicating that the QoS prediction accuracy is improved by number of training samples.

TABLE I. Comparison Of Prediction Accuracy

Methods	Response-time		Throughput	
	Matrix density		Matrix density	
	5%	10%	5%	10%
UPCC	0.5858	0.5615	0.5068	0.4707
NIMF	0.5494	0.5247	0.4561	0.4333
MatC	0.3976	0.3645	0.3652	0.3569
NRMC	**0.3587**	**0.3201**	**0.3234**	**0.3065**

IV. Conclusion

In this paper, we propose a $\ell_{2,1}$-norm regularized matrix completion (NRMC) approach to predict the missing QoS values and simultaneously correct the corrupted ones in support for QoS-based web services selection. We have shown through simulation results that NRMC outperformed other well-known prediction methods. Our future work is to implement the QoS prediction system and deploy it on the Internet.

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