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CSCWD 2016

A User Dependent Web Service QoS Collaborative Prediction Approach Using Neighborhood Regularized Matrix Factorization

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Nanchang, China
May 05, 2016

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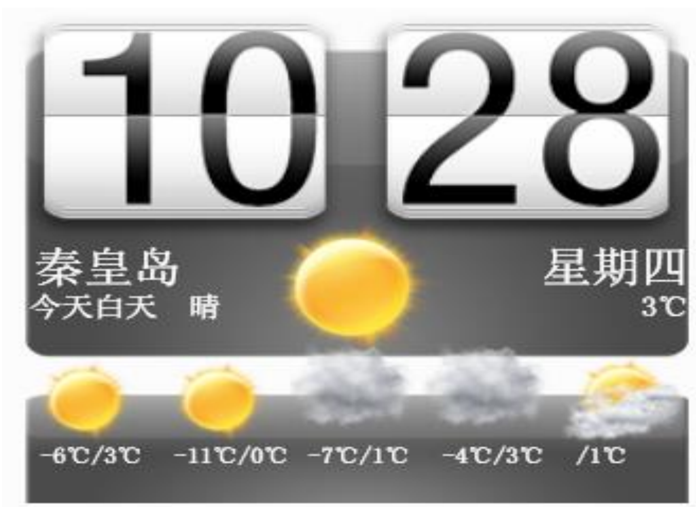
1 Motivation

- **Web service:** reusable, self-describing and loosely coupled Internetware designed to construct complex distributed systems



WPF C# call Sina Weather service

Flex call www.webxml.com.cn Weather service

http://php.weather.sina.com.cn/xml.php?city=%B1%B1%BE%A9&password=DJOYnieT8234jlsK&day=0

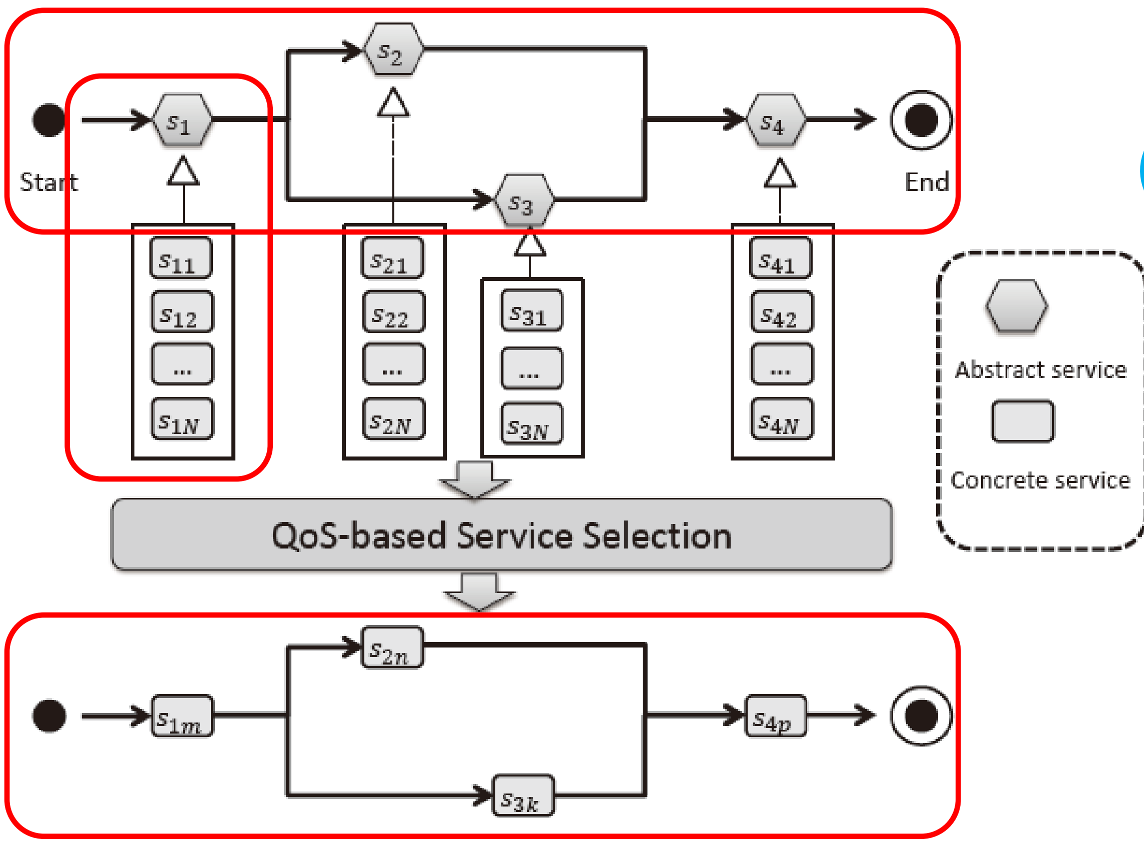
http://webservice.webxml.com.cn/WebServices/WeatherWS.asmx/getWeather

1 Motivation

Web Services Components

1 Motivation

- **Web service composition:** build service-oriented systems using existing Web service components



How to select Web services

1 Motivation

Quality-of-Service (QoS)

- Response time
- Throughput
- Failure probability
- …

Predicting the unknown values is necessary

	s_1	s_2	s_3	s_4	s_5
u_1	0.433	?	0.305	0.546	?
u_2	0.434	?	0.238	?	0.69
u_3	?	3.905	?	?	1.437
u_4	0.56	0.731	?	0.647	?
u_5	0.577	?	?	0.636	?

Challenges

- A user has only called a few services before
- Testing all the services one by one is time consuming
- Web services QoS may vary in different network condition
- …

2 Related Work

- Collaborative filtering(CF) based QoS prediction

Neighborhood-based approaches

- UPCC [Shao et al. 2007]
- IPCC, UIPCC [Zheng et al. 2011]

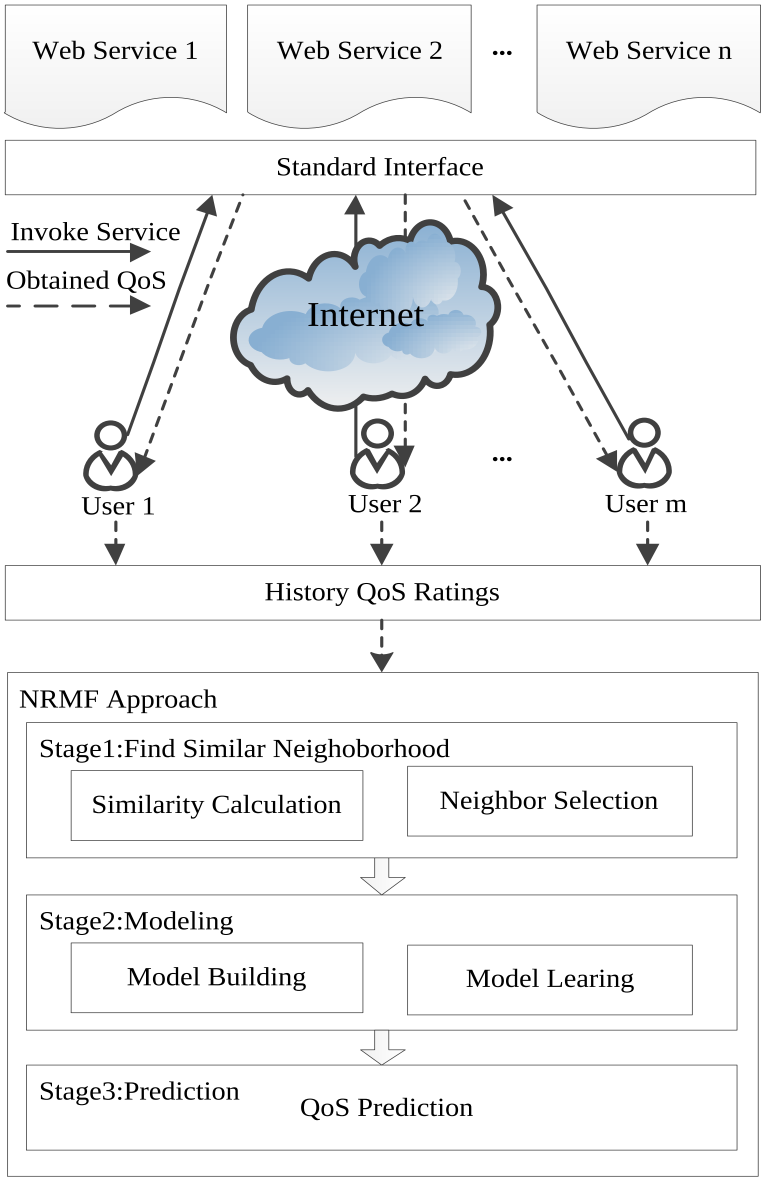
Suffer from the sparsity of available historical QoS data,

Model-based approaches

- MF with regularization terms[Lo et al. 2012]
- NIMF[Zheng et al. 2013]

Alleviate the sparsity issue

3 Architecture



a. Service users invoke Web services across the standard interface by the Internet, and they share the observed QoS values to a system for QoS prediction

b. Based on the shared QoS ratings, user similarity and Web service similarity are calculated separately for corresponding neighborhood selection.

c. integrated with user-side regularization and service-side regularization terms, optimization problem, iterative algorithm

d. QoS predictions are made by the inner product of learned predictive model for further Web service recommendation and fault-tolerant computing.

4 Approach

- **Neighbor Selection** based on significant similarity
  - **Similarity Calculation PCC(Person Correlation Coefficient)**
    - **User PCC**

$$sim'(u,v)=\frac{\sum_{s\in S_{uv}}(r_{u,s}-\overline{r}_u)(r_{v,s}-\overline{r}_v)}{\sqrt{\sum_{s\in S_{uv}}(r_{u,s}-\overline{r}_u)^2}\sqrt{\sum_{s\in S_{uv}}(r_{v,s}-\overline{r}_v)^2}}$$

    - **Service PCC**

$$sim'(s,t)=\frac{\sum_{u\in U_{st}}(r_{u,s}-\overline{r}_s)(r_{u,t}-\overline{r}_t)}{\sqrt{\sum_{u\in U_{st}}(r_{u,s}-\overline{r}_s)^2}\sqrt{\sum_{u\in U_{st}}(r_{u,t}-\overline{r}_t)^2}}$$

Are these PCCs OK for neighbor selection ?

4 Approach

- **Neighbor Selection** based on significant similarity
  - **Significant PCC**

$$sim(u,v) = |S_{uv}| \geq 2 \quad ? \quad \frac{|S_{uv}|}{|S_{uv}| + \alpha} * sim'(u,v) \quad : \quad 0$$

$$sim(s,t) = |U_{st}| \geq 2 \quad ? \quad \frac{|U_{st}|}{|U_{st}| + \alpha} * sim'(s,t) \quad : \quad 0$$

overestimate the similarity of users who are actually not similar but happen to have similar QoS experience on a few co-invoked Web services

  - **Neighbor Selection**

$$N(u) = \{v \mid v \in Top - K(u), sim(u,v) > 0, v \neq u\}$$

$$N(s) = \{t \mid t \in Top - K(s), sim(s,t) > 0, t \neq s\}$$

4 Approach

- **Model building** with selected neighbors

Considering the biases of user & service

$$R \approx U^T S \qquad \hat{r}_{u,s} = p_u^{\ T} q_s$$

The influence of MF model

$$\hat{r}_{u,s} = (1-\beta)(b_a + b_u + b_s) + \beta p_u^{\ T} q_s$$

Minimize this value

Diff. between historical records and predicted values

$$L = \min \frac{1}{2} \sum_{u=1}^{m} \sum_{s=1}^{n} I_{u,s} (r_{u,s} - \hat{r}_{u,s})^2$$

$$+ \frac{\lambda}{2} \left(|S_u|^{-\frac{1}{2}} \|b_u\|_F^2 + |U_s|^{-\frac{1}{2}} \|b_s\|_F^2 + |S_u|^{-\frac{1}{2}} \|p_u\|_F^2 + |U_s|^{-\frac{1}{2}} \|q_s\|_F^2 + \right.$$

$$\left. \sum_{u=1}^{m} \sum_{v \in N(u)} |N(u)|^{-\frac{1}{2}} sim(u,v) \|p_u - p_v\|_F^2 + \sum_{s=1}^{n} \sum_{t \in N(s)} |N(s)|^{-\frac{1}{2}} sim(s,t) \|q_s - q_t\|_F^2 \right)$$

The influence of user neighborhood

The influence of service neighborhood

4 Approach

- **Model learning** with stochastic gradient decent algorithm

$$e = r_{u,s} - \hat{r}_{u,s}$$

$$b_u = b_u + \gamma(e(1-\beta) - \lambda |S_u|^{-\frac{1}{2}} b_u)$$

$$b_s = b_s + \gamma(e(1-\beta) - \lambda |U_s|^{-\frac{1}{2}} b_s)$$

$$p_u = p_u + \gamma(e\beta q_s - \lambda |S_u|^{-\frac{1}{2}} p_u - \lambda \sum_{v \in N(u)} |N(u)|^{-\frac{1}{2}} sim(u,v)(p_u - p_v))$$

$$q_s = q_s + \gamma(e\beta p_u - \lambda |U_s|^{-\frac{1}{2}} q_s - \lambda \sum_{t \in N(s)} |N(s)|^{-\frac{1}{2}} sim(s,t)(q_s - q_t))$$

Iterating every non-empty entry in user-service matrix R until convergence

5 Experiment

- **Dataset**
  - 1,974,675 response time records of 5825 Web service from 339 distributed users in 24 countries.
  - Experiments are conducted on Windows 64bit OS, 3.4GHz processor, 8GB RAM.
- **Metrics**
  - MAE: to measure the average prediction accuracy.

$$MAE = \frac{1}{N}\sum \left| r_{u,s} - \hat{r}_{u,s} \right|$$

  - RMSE: presents the deviation of the prediction error, to detect relatively large errors.

$$RMSE = \sqrt{\frac{1}{N}\sum \left| r_{u,s} - \hat{r}_{u,s} \right|^2}$$

5 Experiment

Comparison (smaller value indicates better accuracy)

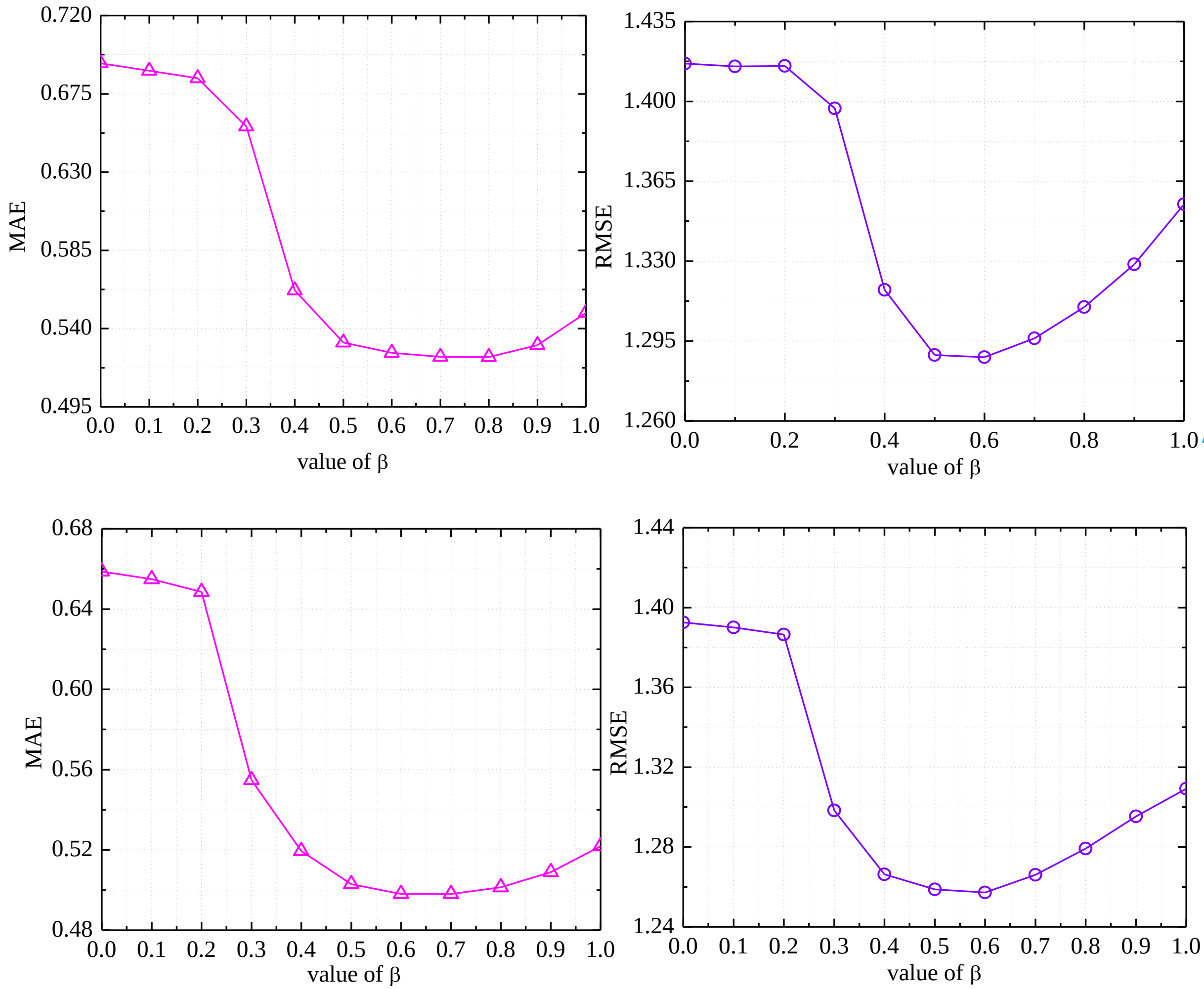
	Density	UMEAN	IMEAN	UPCC	IPCC	UIPCC	NMF	NIMF	NRMF
MAE	3%	0.8787	0.8369	0.6948	0.7195	0.6735	0.6337	0.6182	**0.5522**
	5%	0.8736	0.7626	0.6994	0.7193	0.6698	0.5985	0.5761	**0.5256**
	7%	0.8734	0.7366	0.6957	0.7096	0.6639	0.5805	0.5560	**0.5139**
	10%	0.8695	0.7136	0.6716	0.6970	0.6138	0.5623	0.5359	**0.4970**
RMSE	3%	1.8555	1.6369	1.5562	1.5614	1.5434	1.5206	1.5051	**1.3491**
	5%	1.8541	1.5742	1.4952	1.5289	1.4607	1.4206	1.4547	**1.2908**
	7%	1.8519	1.5522	1.4247	1.5090	1.4274	1.3498	1.3443	**1.2708**
	10%	1.8527	1.5399	1.4248	1.4586	1.3916	1.3340	1.3241	**1.2564**

denser training matrix provides more ratings information that can be utilized to benefit the prediction performance

ULMF outperforms the other methods

5 Experiment

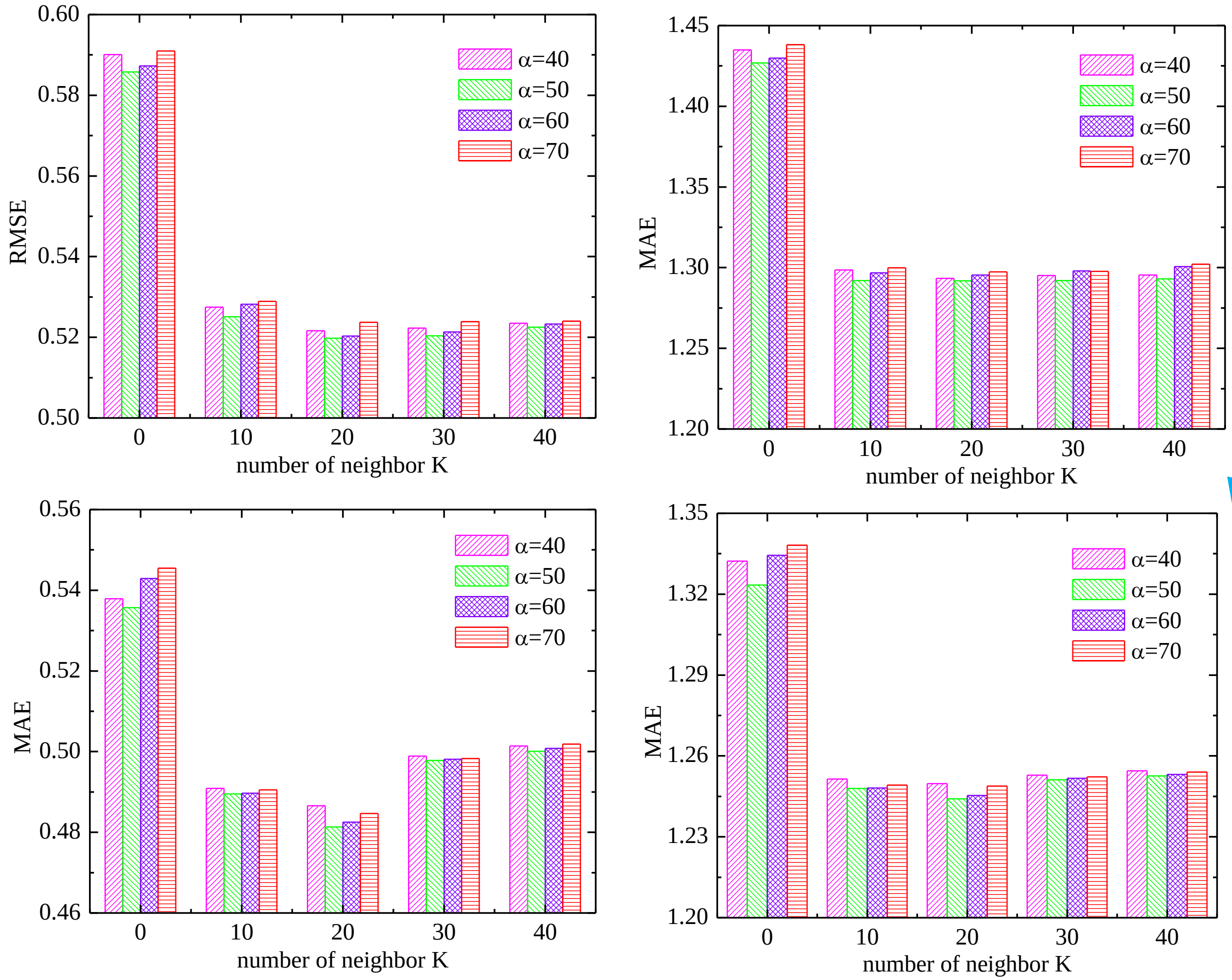
- **The impact of parameter β** **adjust the influence of biases**



The Impact of β:
1 optimal β setting can obtain better prediction accuracy
2 fusing of user and service biases will improve prediction accuracy

5 Experiment

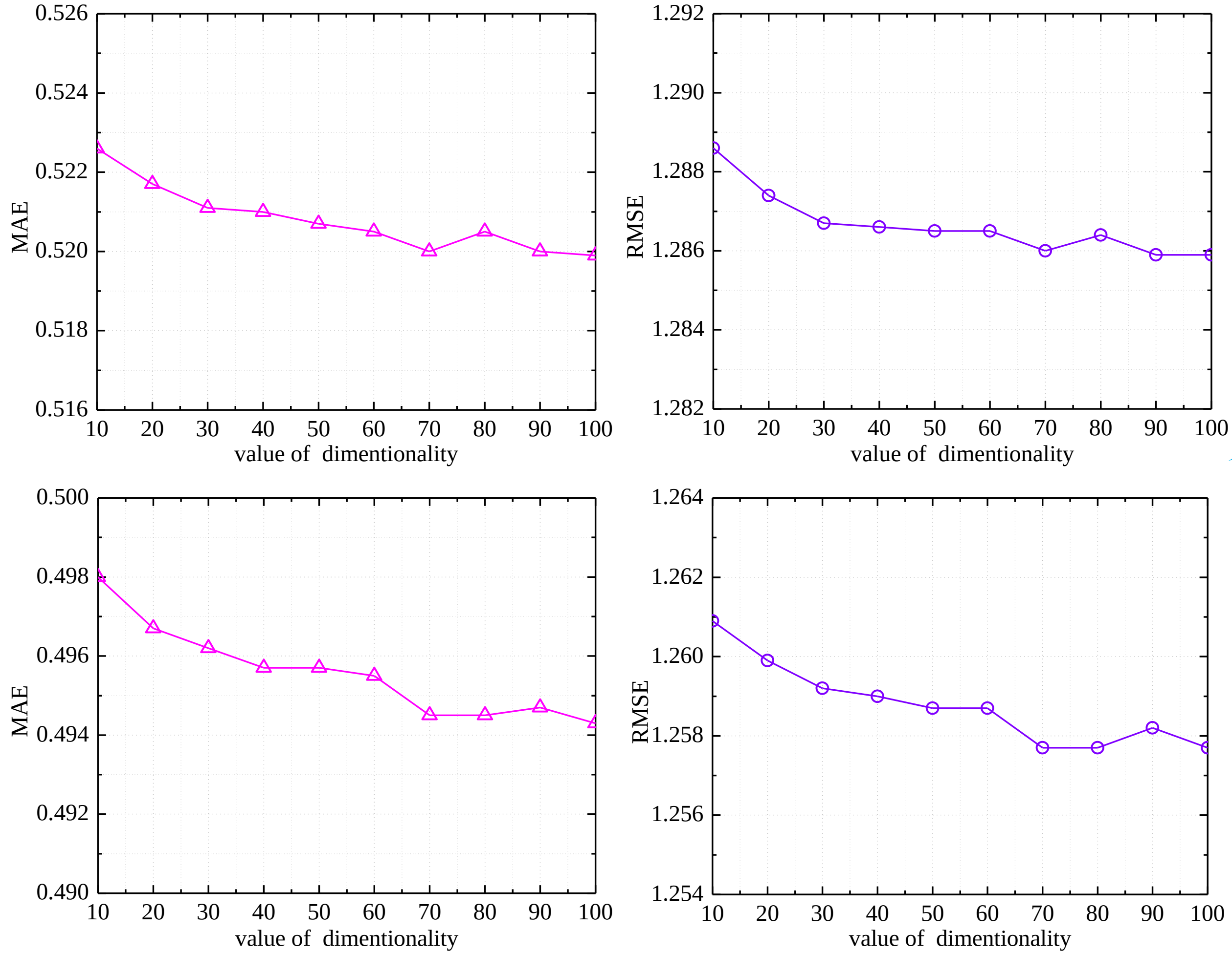
impact of Neighbor Number K and Shrinkage α



(1) K=0, leveraging the wisdom of implicit neighborhood is effective to improve prediction accuracy of NRMF
(2)Optimal Top-K and α can be selected to achieve best performance.

5 Experiment

The impact of dimensionality *d*



NRMF is less sensitive to the value of dimensionality.

6 Conclusion and future work

Conclusion

- NRMF :the similar neighborhoods of users and Web services can provide meaningful information for more accurate Web service QoS prediction
- significant similarity weight calculation method and bias combination strategy were adopted and proved to be effective in improving prediction performance

Future work

- Extend our model with other implicit information such as location information, social information, expecting for better prediction performance
- Considering the importance of a user who often contribute to the final results of a services

Thank You !