燕山大學
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CCSCW 2015

ULMF: Web Service QoS Collaborative Prediction with Explicit Ratings and Implicit User Location

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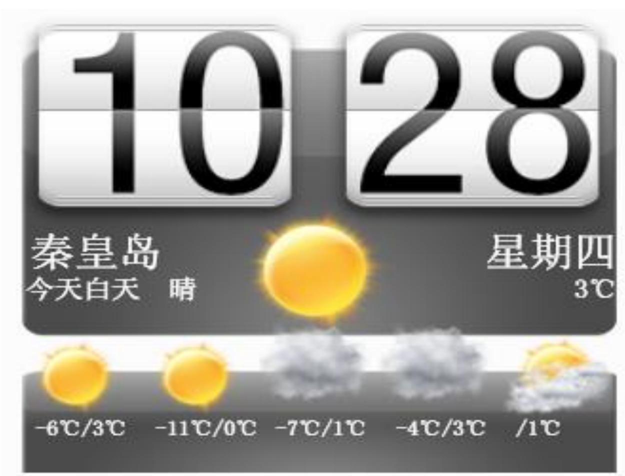
OUTLINE

1 Motivation

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



WPF C#调用新浪天气服务

Flex调用www.webxml.com.cn站点天气服务

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

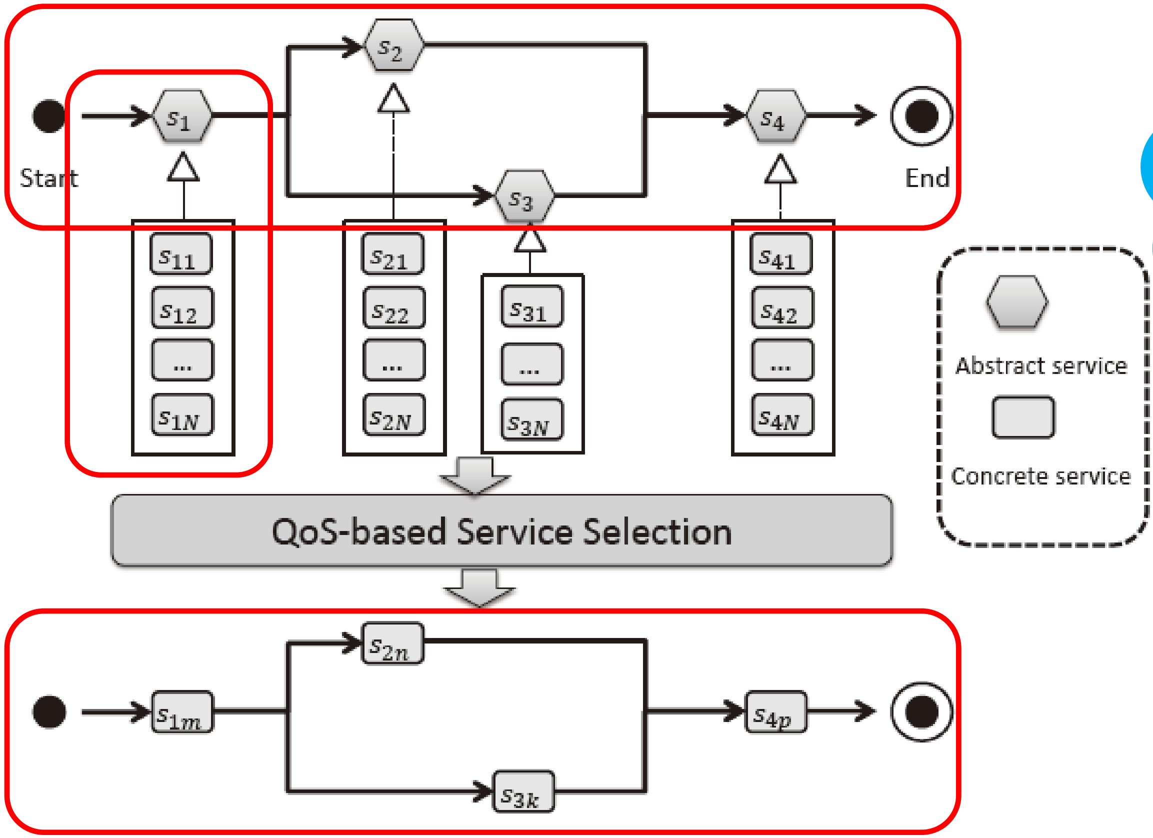
1 Motivation

Web Services Components

AIR CHINA
中国国际航空公司

1 Motivation

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



1 Motivation

Predict the unknown values

- **Quality-of-Service (QoS)**
  - Response time
  - Throughput
  - Failure probability
  - …

	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
  - Calling 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,
  Especially run into malfunction for new users

  Model-based approaches

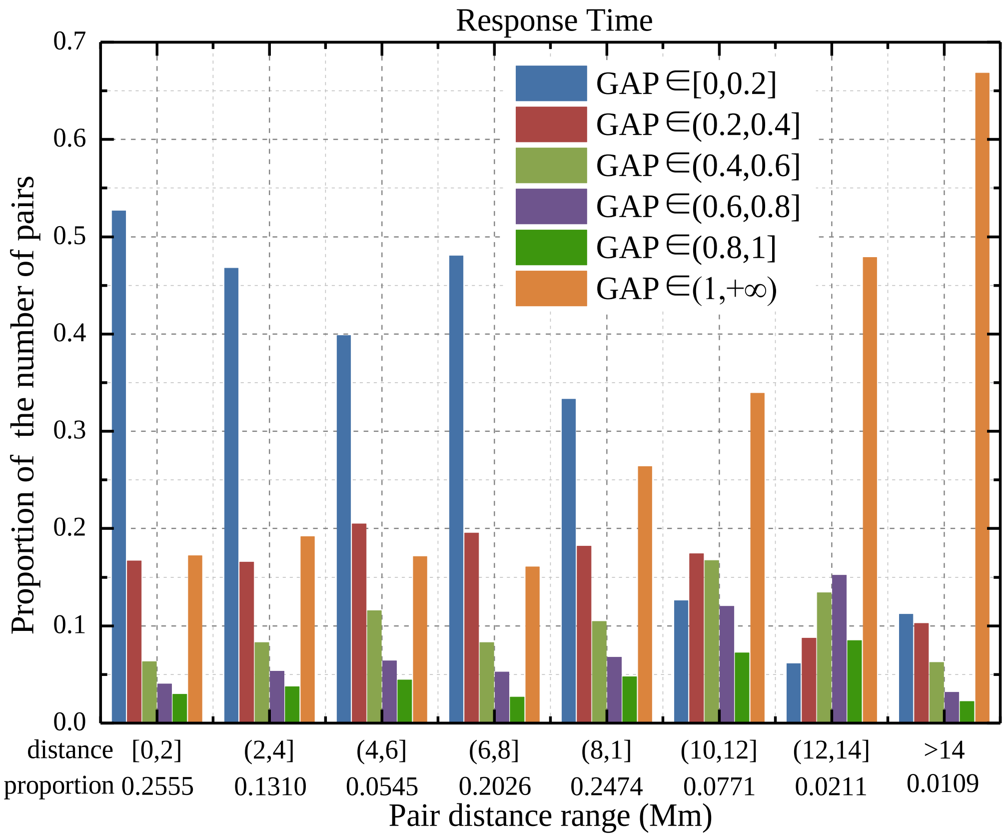
  - MF with regularization terms[Lo et al. 2012]
  - NIMF[Zheng et al. 2013]

  Address the cold-start issue

2 Related Work

User Location Information is not carefully concerned

Why consider user location information?



Distribution of pairs in different distance range

$$GAP(\overline{r}_u, \overline{r}_v) = Abs(\overline{r}_u - \overline{r}_v) / Min(\overline{r}_u, \overline{r}_v)$$

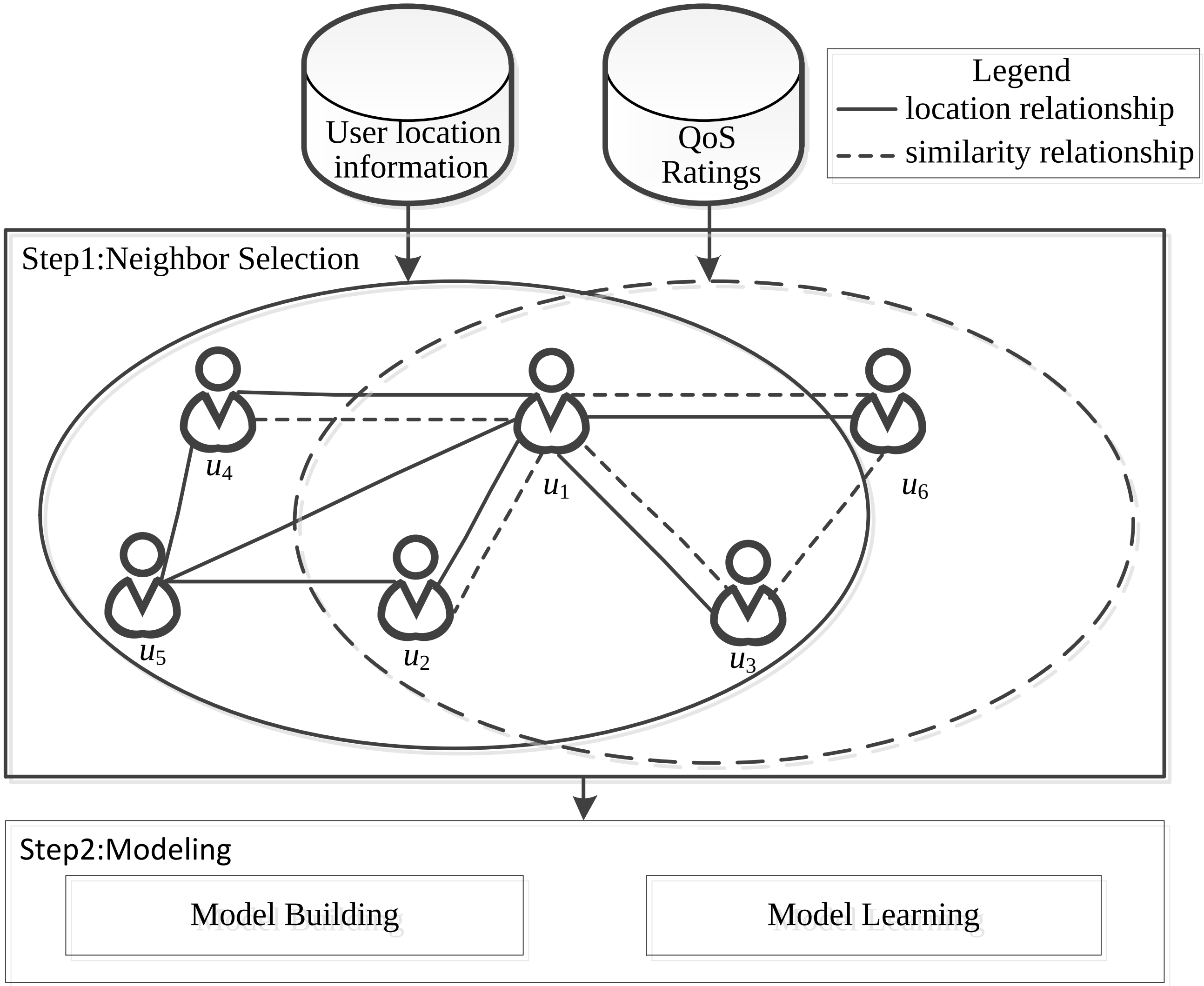
Observation

A user pair's *GAP* has a positive correlation with user pair's distance

Motivation

The smaller distance, the more similar QoS ratings; the larger distance, the more dissimilar QoS ratings.

3 Architecture



a. collecting user location info and monitoring the QoS info

b. neighbor selection based on both distance and similarity

c. selected neighbors are integrated back into matrix factorization model

4 Approach

- **Neighbor Selection** based on distance and similarity
  - **Distance Calculation**

$$d(u,v) = RADIUS * arccos(\sin(lat_u') * \sin(lat_v') * cos(lon_u' - lon_v') \\ + cos(lat_u') * cos(lat_v')) * PI / 180$$

  - **Preliminary Filtering**

$$N(u) = \{v \mid Top - K(List(u)), u \neq v\}$$

Are these neighbors OK ?

4 Approach

- **Neighbor Selection** based on distance and similarity
  - **Similarity Calculation PCC(Person Correlation Coefficient)**

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

  - **Secondary Filtering**

$$EN(u)=\begin{cases}\{v \mid v\in N(u)\}, & u\ \ is\ \ a\ \ new\ \ comer\\ \{v \mid sim(u,v)>0, v\in N(u)\}, & otherwise\end{cases}$$

4 Approach

- **Model building** with selected neighbors

Considering the biases of user & service

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

The influence of neighborhood

$$\hat{r}_{u,s} = (1-\beta)(\mu + b_u + b_s) + \beta q_s^{\,T}\Big(p_u + |EN_u|^{-\frac{1}{2}} \sum_{v \in EN_u} n_v\Big)$$

$$L = \min \frac{1}{2} \sum_{u=1}^{m} \sum_{s=1}^{n} I_{u,s} (r_{u,s} - \hat{r}_{u,s})^2$$
$$+ \frac{\lambda}{2}\Big(|S_u|^{-\frac{1}{2}} \|b_u\|_F^2 + |U_s|^{-\frac{1}{2}} \|b_s\|_F^2 + |S_u|^{-\frac{1}{2}} \|p_u\|_F^2 + |U_s|^{-\frac{1}{2}} \|q_s\|_F^2 + \sum_{v \in EN_u} |EN_v|^{-\frac{1}{2}} \|n_v\|_F^2\Big)$$

Diff. between historical records and predicted values

Minimize this value

Regularization terms

4 Approach

- **Model learning** with gradient decent algorithm

$$b_u' = b_u - \gamma \frac{\partial L}{\partial b_u}, \qquad -\frac{\partial L}{\partial b_u} = \sum_{s=1}^{n} I_{u,s}(r_{u,s} - \hat{r}_{u,s})(1-\beta) - \lambda |S_u|^{-\frac{1}{2}} b_u$$

$$b_s' = b_s - \gamma \frac{\partial L}{\partial b_s}, \qquad -\frac{\partial L}{\partial b_s} = \sum_{u=1}^{m} I_{u,s}(r_{u,s} - \hat{r}_{u,s})(1-\beta) - \lambda |U_s|^{-\frac{1}{2}} b_s$$

$$p_u' = p_u - \gamma \frac{\partial L}{\partial p_u}, \qquad -\frac{\partial L}{\partial p_u} = \sum_{s=1}^{n} I_{u,s}(r_{u,s} - \hat{r}_{u,s})\beta q_s - \lambda |S_u|^{-\frac{1}{2}} p_u$$

$$q_s' = q_s - \gamma \frac{\partial L}{\partial q_s}, \qquad -\frac{\partial L}{\partial q_s} = \sum_{u=1}^{m} I_{u,s}(r_{u,s} - \hat{r}_{u,s})\beta (p_u + |EN_u|^{-\frac{1}{2}} \sum_{v \in EN_u} n_v) - \lambda |U_s|^{-\frac{1}{2}} q_s$$

$$n_v' = n_v - \gamma \frac{\partial L}{\partial n_v}, \qquad \forall v \in EN_v, -\frac{\partial L}{\partial n_v} = \sum_{s=1}^{n} I_{u,s}(r_{u,s} - \hat{r}_{u,s})\beta |EN_u|^{-\frac{1}{2}} q_s - \lambda |EN_v|^{-\frac{1}{2}} n_v$$

Gradient Descent

5 Experiment

Dataset

- 1,974,675 response time records of 5825 Web service from 339 distributed users in 24 countries.
- Longitude and latitude geographic information of 339 users were extracted from userlist.txt file.

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	SVD++	NIMF	ULMF
MAE	2.5%	0.8792	0.7382	0.7639	0.7884	0.6965	0.7616	0.6929	0.6715	**0.6189**
	5%	0.8786	0.7032	0.6955	0.7178	0.6173	0.6778	0.6558	0.6159	**0.5329**
	7.5%	0.8749	0.6941	0.6888	0.7131	0.5721	0.6691	0.6444	0.5517	**0.5036**
	10%	0.8716	0.6884	0.6876	0.7047	0.5395	0.6551	0.6417	0.5023	**0.4778**
RMSE	2.5%	1.8625	1.6467	1.7278	1.7934	1.5239	1.9411	1.7066	1.6198	**1.5674**
	5%	1.8579	1.5746	1.5025	1.5333	1.4916	1.7936	1.4490	1.4808	**1.3962**
	7.5%	1.8588	1.5599	1.4813	1.5120	1.4557	1.7818	1.4343	1.3682	**1.3054**
	10%	1.8596	1.5485	1.4661	1.4988	1.4195	1.7701	1.4309	1.3001	**1.2526**

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

ULMF outperforms the other methods

5 Experiment

- **The influence of code-start users**
  - 200:139

Location-aware neighbors' information enabling UMLF to learn more reliable user latent features than rating-only matrix factorization

COMPARISON WITH COLD-START USERS

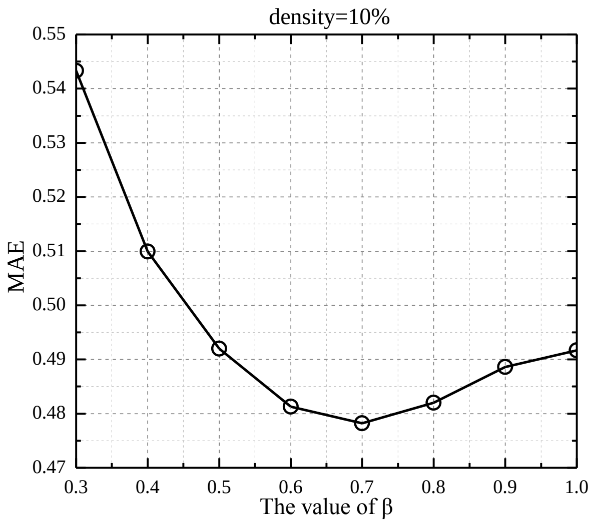
	Density	IMEAN	NMF	SVD++	ULMF
MAE	2.5%	0.7141	0.8447	0.7125	**0.6324**
	5%	0.6921	0.8109	0.7023	**0.5925**
	7.5%	0.6758	0.8001	0.6802	**0.5891**
	10%	0.6790	0.7753	0.6688	**0.5739**
RMSE	2.5%	1.6356	2.0809	1.6787	**1.6025**
	5%	1.5712	2.0173	1.6220	**1.5220**
	7.5%	1.5576	1.9621	1.5948	**1.5129**
	10%	1.5346	1.9495	1.5203	**1.4812**

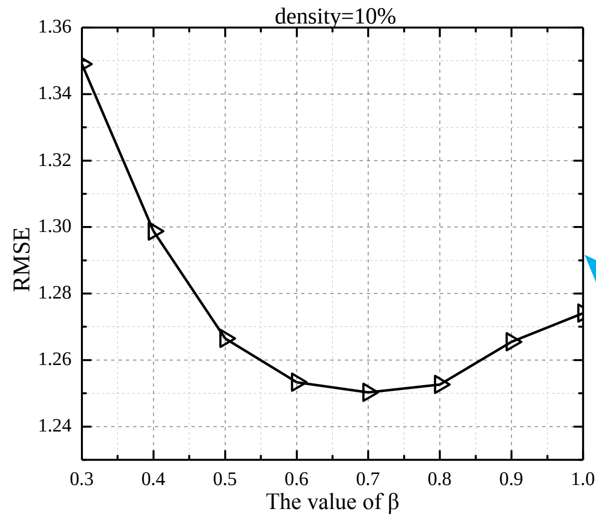
denser training matrix provides more ratings information that can be utilized to benefit the prediction performance

ULMF outperforms the other methods

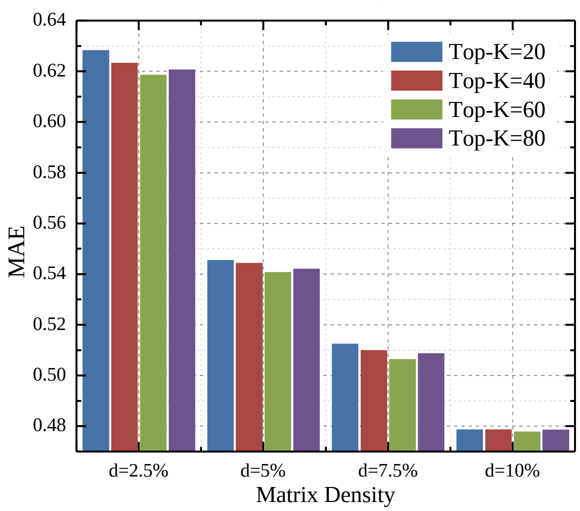
5 Experiment

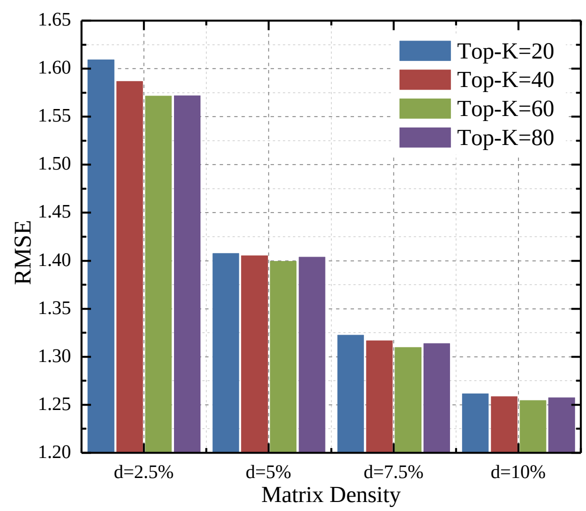
The impact of parameters





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

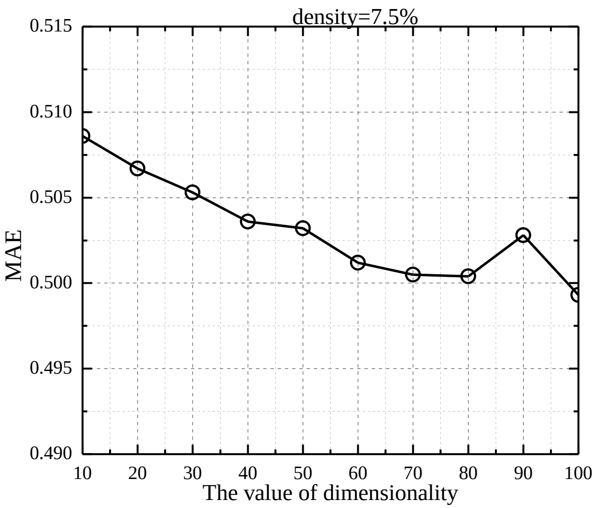


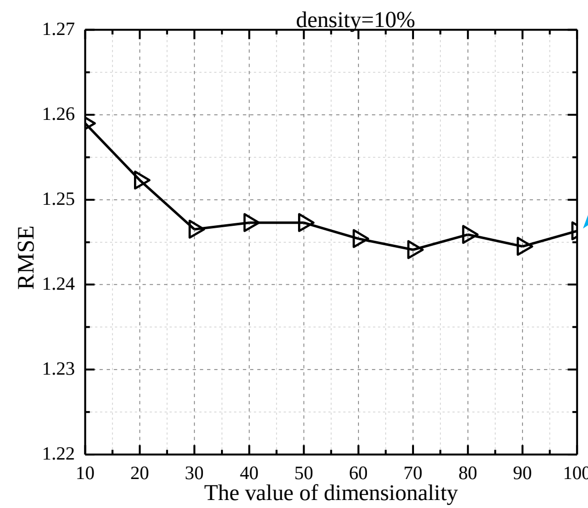


The Impact of Top-K:
Optimal Top-K can be selected to achieve best performance.

5 Experiment

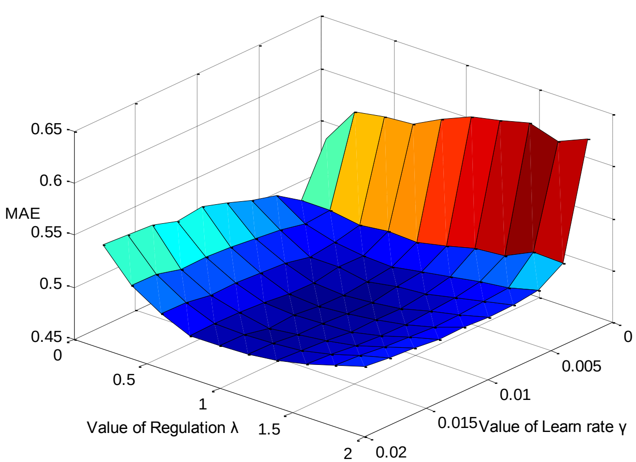
The impact of parameters

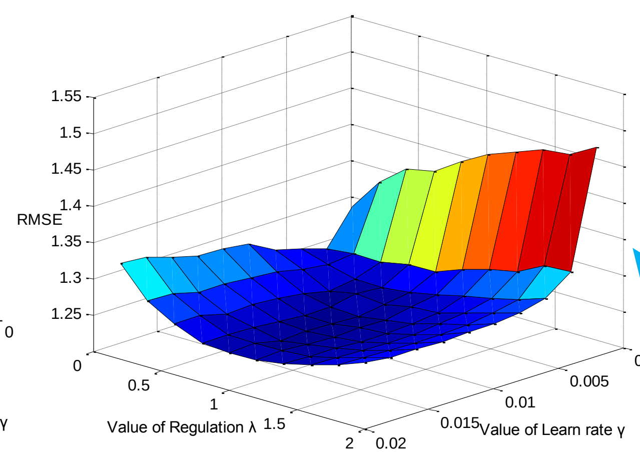




The Impact of dimensionality :

ULMF is less sensitive to the value of dimensionality.





The Impact of λ and γ:

Optimal λ and γ can be selected to achieve best performance.

6 Conclusion and future work

Conclusion

- Analyze the relationship of users and neighbors' QoS ratings under the concept of geographic distance relationship
- Cooperate location information with matrix factorization approach
- Outperform the other existing approaches, as well as perform well under cold start situation.

Future work

- Support service-side location information mining and extend our model to support service location-awareness for better prediction
- Find out some other additional information(time, trust) except location to improve the prediction outcome

Thank You !