Context-Aware Service Recommendation

[Recommender System and Service Computing]

Knowledge Engineering & E-Commerce

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Outline

- **Background**
  - (Web) Service
  - Service Recommendation
- **Context information**
  - User Context Information
  - Service Context Information
- **Context-aware feature learning**
  - User context-aware features learning
  - Service context-aware features learning
- **Experiment**
  - Experimental Result
  - Performance Comparison
- **Reference**

Background
➔ (Web) service

- **(Web) Service**
  - A (Web) service is a self-describing programmable application used to achieve interoperability and accessibility over a network

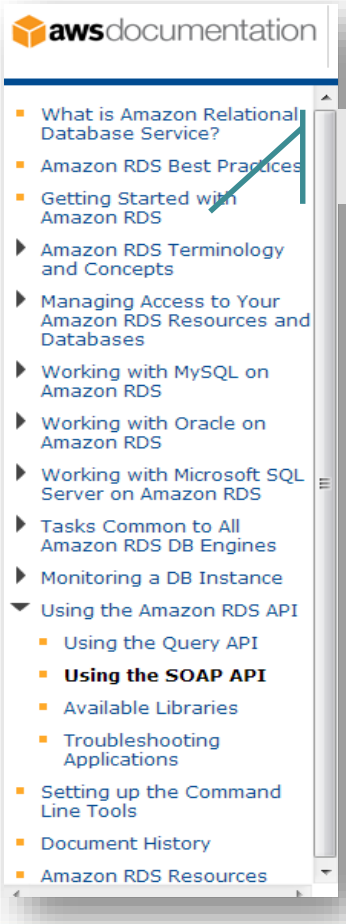
*** Traditional (Web) Service ==**

- WSDL: an XML file following some standards
- Interface: a function
- SOAP: Simple Object Access Protocol

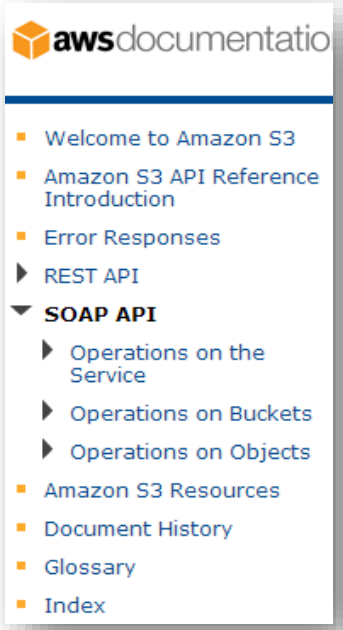
*** Modern (Web) Service ==** an independent **resource** in a network or Internet

Background
➔ (Web) service

- **Example 1**
  - Amazon Database Service
  - Amazon Storage Service → AWS
  - Windows Aure Storage Service



Amazon Database Service



Amazon Simple Storage Service

Background
➔ (Web) service

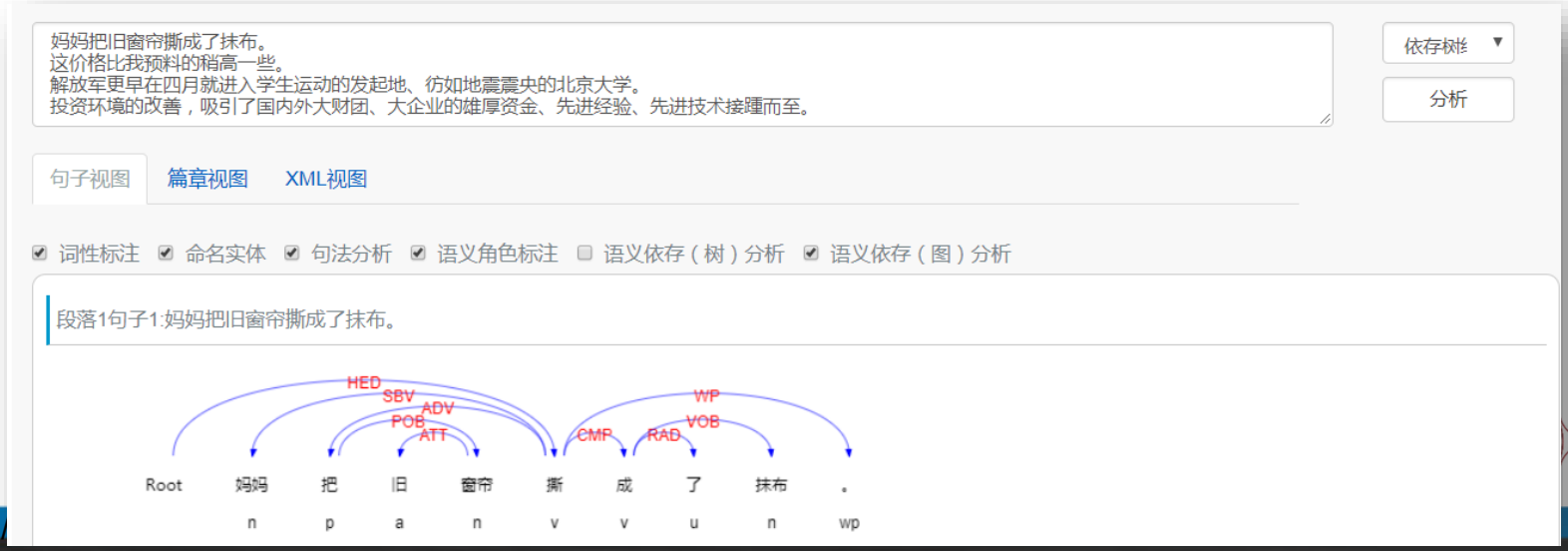
- **Example 2**
  - Open API:
    - Douban, Sina Weibo, Baidu Map, Xiami…
    - Facebook, Twitter, eBay, Google Map, Bing Map…

Background
➔ (Web) service

- **Example 3:**
  - Some other resources in Internet, a network or a system
    - Online tools

      Google docs, Slideshare PPT, Online Latex, Online Mail,

      Online Storage, Online Bus Query, Online NLP



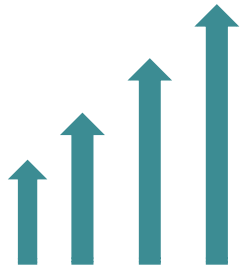
Background
➔ (Web) service

- **Service Computing**
  - a sub-field of software engineering and distributed computing
  - Research topics: service selection, service composition, service discovery, service recommendation, service orchestration, etc.
  - Conference: IEEE ICWS (Inter. Conf. Web Services), ICSOC (Inter. Conf. Service-oriented Computing)
  - Journal: IEEE trans. Service Computing (TSC)
  - CCF: CCF Technical Committee on Service Computing (CCF TCSC)

Background
→ service recommendation

- **Service explosion**
  - Cloud computing (a lot of applications are provided as services)
  - Mobile computing (a lot of apps are based on open apis)

  → the number of (Web) services is exploding



- **Challenge**
  - People want to use the ‘best’ service, but people don’t know where the ‘best’ one is.
  - Is there a service suitable for everyone? No → Why? → Context

Background
➔ service recommendation

- So the problem is : which one should I use?

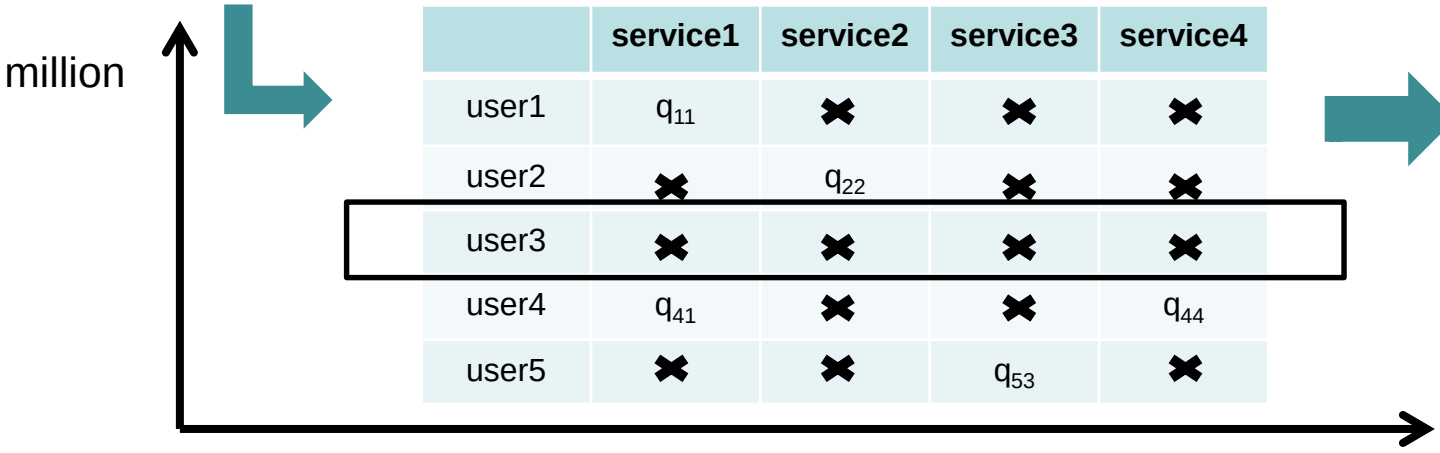
- **Measure / Criteria**
  - Quality of Service, QoS
  - E.g., response time, throughput, reliability, etc.

Personalization & Prediction

- Similar to the rating prediction problem in e-commerce systems
- User -<>- User; Item -<>- Service; QoS -<>- Rating

Background
→ service recommendation

- **Formalization of the Problem**
  - Personalized QoS prediction
  - User-Service Invocation Matrix



	service1	service2	service3	service4
user1	q_{11}	✖	✖	✖
user2	✖	q_{22}	✖	✖
user3	✖	✖	✖	✖
user4	q_{41}	✖	✖	q_{44}
user5	✖	✖	q_{53}	✖

Sufficient Features + Effective Model

- **Challenge**
  - Data Sparsity → Cold Start Problem
  - Large Scale → Feasibility

Cold-Start Problem

Context-aware recommendation

- **Contextual Features Selection**
  - Basis: factors dominating QoS: ***physical configuration***

- **Feature Modeling**
  - User-User: *Geographical Distance*
  - Service-Service: *Service Provider*

Context-aware recommendation

- **Observation**
  - For the exactly same service or user:

city, town, community

Just the same as browsing in Internet

✓ Users in different locations usually experience different QoS
✓ Users in the same location usually experience similar QoS

✓ Services operated by different providers usually offer different QoS
✓ Services operated by the same providers usually offer similar QoS

- **Assumption:**
  - Users located nearly with each other have similar IT infrastructure
  - Services provided by the same company have similar physical configuration

Context-aware recommendation

- **Probabilistic Matrix Factorization**
  - MF can factorize the high-rank user-service invocation feature space into the joint low-rank feature space
  - $Q=\{q_{ij}\}$: $m \times n$ user-service invocation matrix
  - $U \in R^{d*m}$, $S \in R^{d*n}$: user and service feature matrices

$$q_{ij} \approx U_i^T S_j$$

Inner product of two *d*-rank feature vectors

$$\min L = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(q_{ij} - U_i^T S_j)^2 + \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_S}{2}\|S\|_F^2$$

Regularization Term

Objective Function

Context-aware features learning
➔ User Side

- **User Feature Learning**

$$q_{ij} \approx \hat{q}_{ij} = \alpha U_i^T S_j + (1-\alpha)\sum_{l=1}^{k} w_{il} U_l^T S_j$$

Learned from his/her neighbors' invocation experience

- **New Objective Function**

$$L = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(q_{ij} - (\alpha U_i^T S_j + (1-\alpha)\sum_{l=1}^{k} w_{il} U_l^T S_j))^2 + \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_S}{2}\|S\|_F^2$$

(Stochastic) Gradient Descent ➔ Local Minimum

$$\begin{cases} \dfrac{\partial E}{\partial U_i} = \alpha\sum_{j=1}^{n} I_{ij} S_j (\alpha U_i^T S_j + (1-\alpha)\sum_{l=1}^{k} w_{il} U_l^T S_j - q_{ij}) + \lambda_U U_i \\ \dfrac{\partial E}{\partial S_j} = \sum_{i=1}^{m} I_{ij}(\alpha U_i^T S_j + (1-\alpha)\sum_{l=1}^{k} w_{il} U_l^T S_j - q_{ij}) \times (\alpha U_i + (1-\alpha)\sum_{l=1}^{k} w_{il} U_l) + \lambda_S S_j \end{cases}$$

Context-aware features learning
➔ Service Side

- **Reasonable Combination**

$$q_{ij} \approx \hat{q}_{ij} = \alpha U_i^T S_j + (1-\alpha)\frac{1}{|C(j)|}\sum_{c \in C(j)} U_i^T S_c$$

Learned from its neighbors' invocated experience

- **New Objective Function**

$$L = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(q_{ij} - (\alpha U_i^T S_j + (1-\alpha)\frac{1}{|C(j)|}\sum_{c \in C(j)} U_i^T S_c))^2 + \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_S}{2}\|S\|_F^2$$

(Stochastic) Gradient Descent ➔ Local Minimum

the same with the computation process of ***user-side***

Experiment

- **Preparation**
  - Dataset: real world dataset
  - Matrix Density: 5%~20%
  - Evaluation Metrics: RMSE and MAE
  - Result: average of multiple testing

Approach	Matrix Density (MD)							
	MD=5%		MD=10%		MD=15%		MD=20%	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
UPCC	1.6940	0.7229	1.6101	0.6473	1.4959	0.5674	1.3993	0.5087
IPCC	1.6346	0.7347	1.5439	0.6610	1.4104	0.5813	1.3109	0.5130
UIPCC	1.5837	0.7043	1.4744	0.6208	1.3458	0.5436	1.2594	0.4819
RegionKNN	1.5681	0.6958	1.4554	0.6092	1.3335	0.5343	1.2532	0.4752
Basic-MF	1.4952	0.7251	1.3127	0.5902	1.2671	0.5431	1.2261	0.5078
EMF_F	1.4790	0.7162	1.2955	0.5737	1.2451	0.5316	1.2156	0.5040
NIMF	1.4023	0.6316	1.2702	0.5384	1.2215	0.5164	1.1908	0.4903
SN-EMF	**1.3935**	**0.6273**	**1.2689**	**0.5363**	**1.2276**	**0.5022**	**1.2065**	**0.4872**
UN-EMF	**1.3850**	**0.6139**	**1.2666**	**0.5359**	**1.2207**	**0.5077**	**1.1898**	**0.4900**
U-EMF	**1.3503**	**0.5840**	**1.2548**	**0.5171**	**1.2117**	**0.4909**	**1.1701**	**0.4681**

Memory-based

ML-based

User-side & Service-side

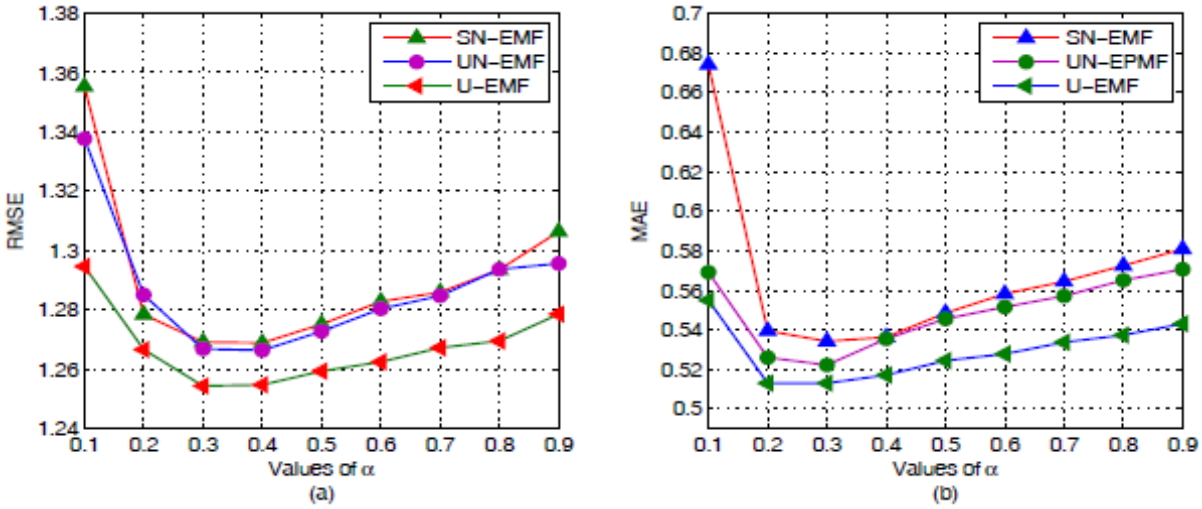
Unification

Our methods

Experiment

Impact of α

- The parameter α controls the individual contributions of the user/service and their neighbors to the predicted value



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Thank You
Q&A