Personalized Transfer of User Preferences for Cross-domain Recommendation

Yongchun Zhu[1,3,4] , Zhenwei Tang[1], Yudan Liu[4], Fuzhen Zhuang[2,5], Ruobing Xie[4],
Xu Zhang[4], Leyu Lin[4], Qing He[1,2]

1.Key Lab of Intelligent Information Processing of Chinese Academy of Sciences (CAS) , Institute of Computing Technology, CAS, Beijing, China

2. Institute of Artificial Intelligence, Beihang University, Beijing 100191, China

3. University of Chinese Academy of Sciences, Beijing, China

4. WeChat Search Application Department, Tencent, China

5. SKLSDE, School of Computer Science, Beihang University, Beijing 100191, China

中国科学院计算技术研究所
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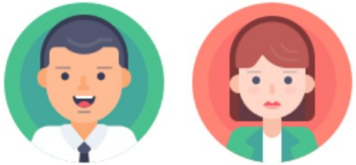
Motivation

Cold-start Problem

How to recommend to these new(cold-start) users?

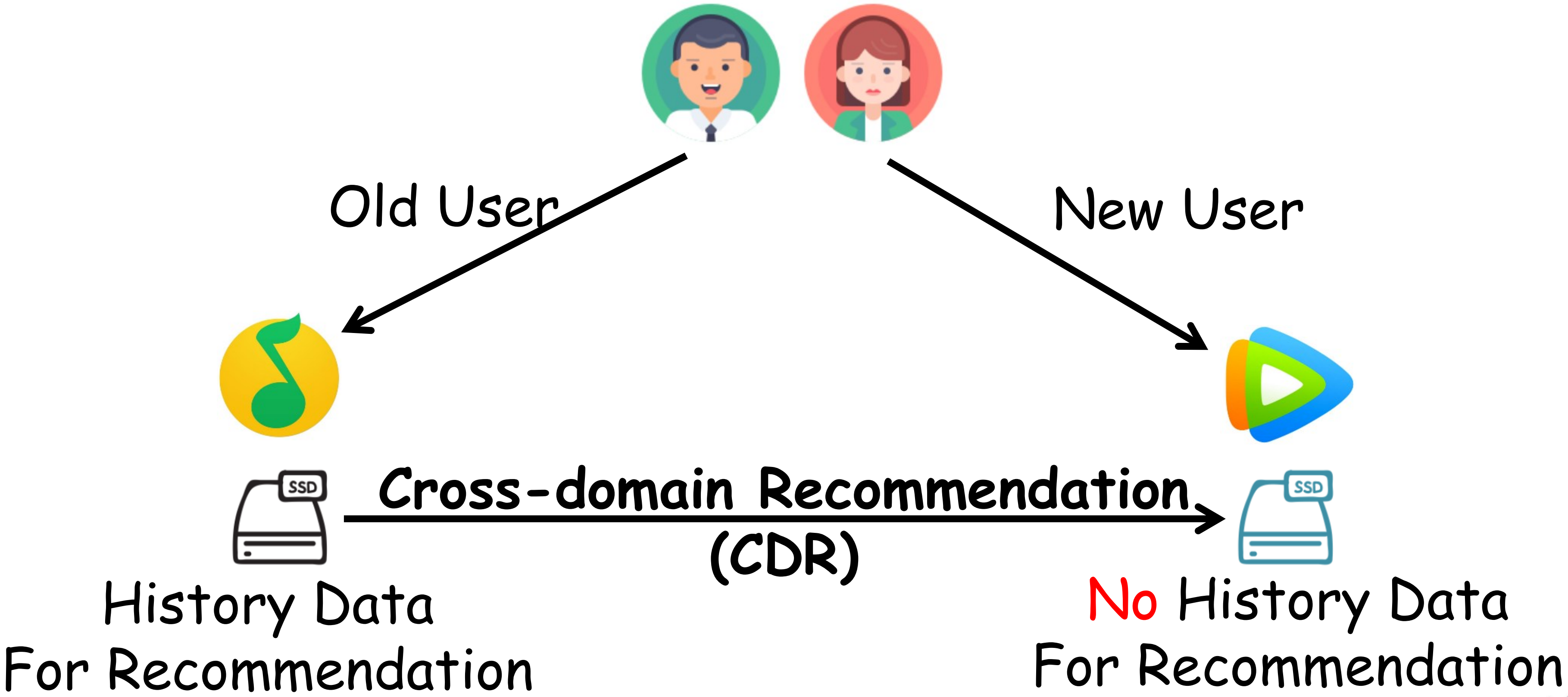


New User

Tencent Video

No History Data For Recommendation

Motivation

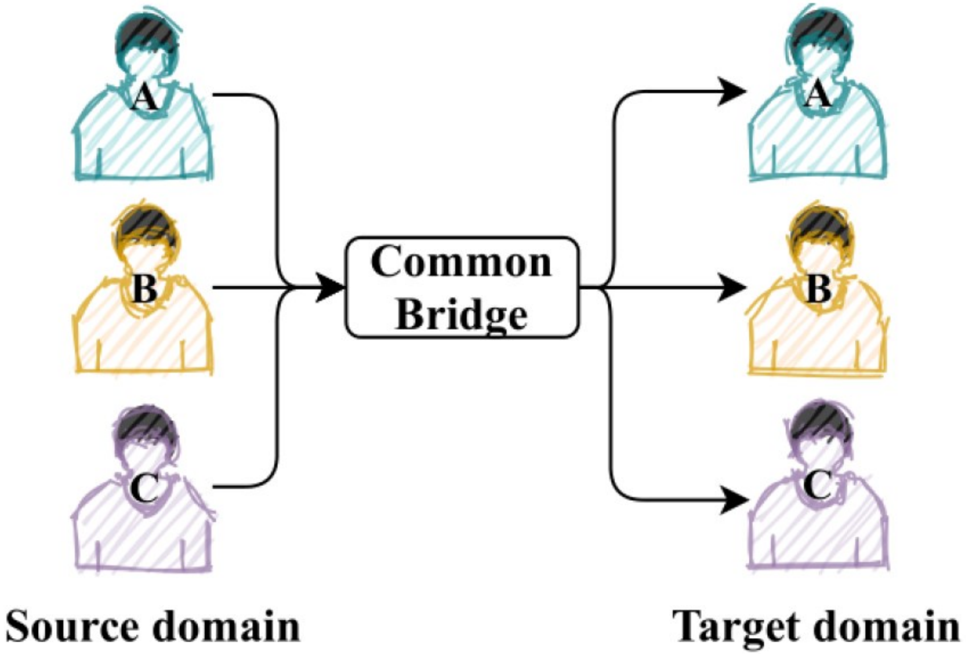


Old User
New User
SSD
Cross-domain Recommendation
(CDR)
SSD
History Data
For Recommendation
No History Data
For Recommendation

Motivation

Cross-domain recommendation aims to **bridge user's preferences** in the source domain and the target domain.

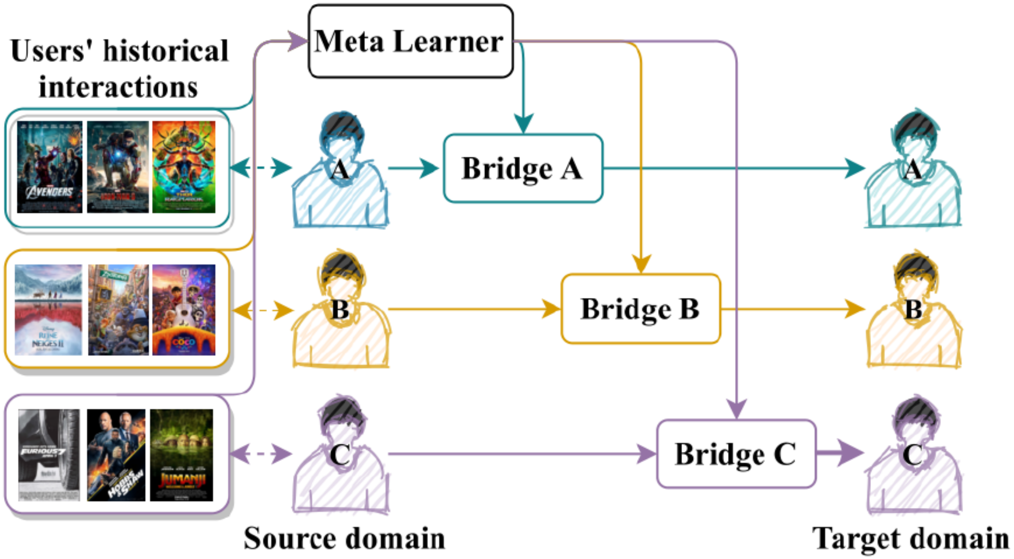
Existing methods assume that all users share the **same preference relationships**. (**Common Bridge**)



Motivation

Challenges

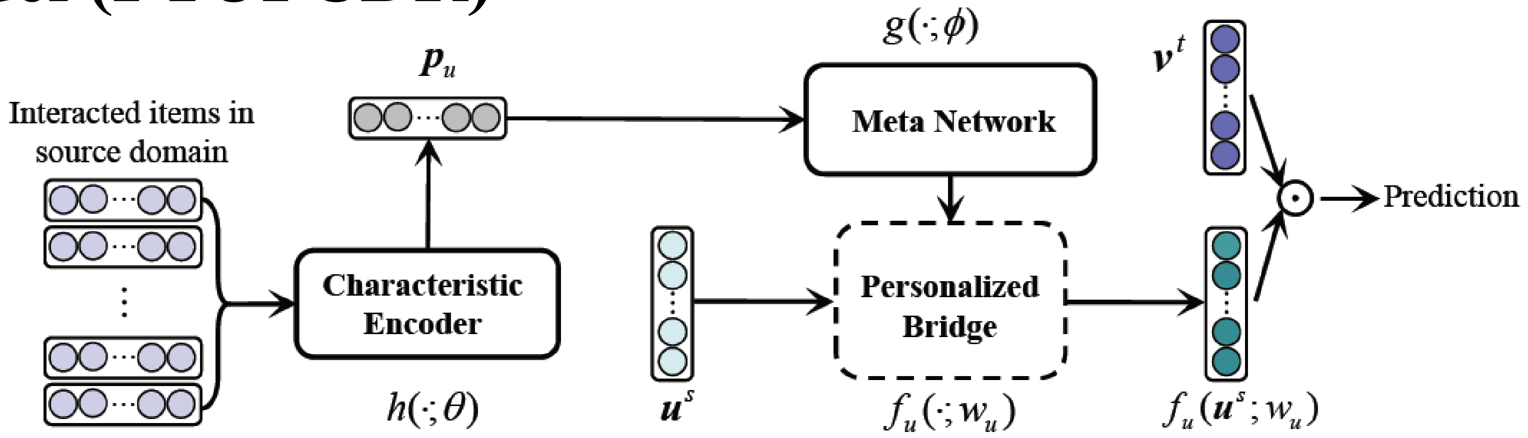
- ☐ Diverse user characteristics
- ☐ Various preference relationships



Solution

- ☐ Personalized Transfer of User Preferences

Model (PTUPCDR)



- Characteristic Encoder

$$p_{u_i} = \sum_{v_j^s \in S_{u_i}} a_j v_j^s,$$

$$a'_j = h(v_j;\theta),$$

$$a_j = \frac{\exp(a'_j)}{\sum_{v_l^s \in S_{u_i}} \exp(a'_l)},$$

- Meta Network

$$\boldsymbol{w}_{u_i} = g(\boldsymbol{p}_{u_i};\phi),$$

- Personalized Bridge

$$f_{u_i}(\cdot;\boldsymbol{w}_{u_i}),$$

- Transformed Embedding

$$\hat{\boldsymbol{u}}_i^t = f_{u_i}(\boldsymbol{u}_i^s;\boldsymbol{w}_{u_i}),$$

Model (PTUPCDR)

- mapping-oriented optimization

$$\mathcal{L} = \sum_{u_i \in \mathcal{U}^o} ||\hat{\boldsymbol{u}}_i^t - \boldsymbol{u}_i^t||^2,$$

- task-oriented optimization

$$\min_{\theta,\phi} \frac{1}{|\mathcal{R}_o^t|} \sum_{r_{ij} \in \mathcal{R}_o^t} (r_{ij} - f_{u_i}(\boldsymbol{u}_i^s; \boldsymbol{w}_{u_i})\boldsymbol{v}_j)^2,$$

Algorithm 1 Personalized Transfer of User Preferences for CDR (PTUPCDR)

Input: $\mathcal{U}^s, \mathcal{U}^t, \mathcal{V}^s, \mathcal{V}^t, \mathcal{U}^o, \mathcal{R}^s, \mathcal{R}^t$
Input: Meta network g_ϕ.
Input: Characteristic encoder h_θ.
Pre-training Stage:
1. Learning a source model which contains $\boldsymbol{u}^s, \boldsymbol{v}^s$.
2. Learning a target model which contains $\boldsymbol{u}^t, \boldsymbol{v}^t$.

Meta Stage:
3. Learning a characteristic encoder h_θ and a meta network g_ϕ by minimizing Equation (7).

Initialization Stage:
4. For a cold-start user u^t in the target domain, we use the transformed embedding $f_{u_i}(\boldsymbol{u}_i^s; \boldsymbol{w}_{u_i})$ as the user's initialized embedding in the target domain.

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Experiments

Datasets

- Amazon review dataset

Metrics: MAE, RMSE

Baselines

- TGT denotes the target MF model, which is trained only using target domain data.
- CMF is an extension of MF. In CMF, the embeddings of users are shared across the source and target domains.
- EMCDR adopts to learn embeddings first and then utilize a network to bridge the user embeddings from the auxiliary domain to the target domain.
- DCDCSR falls into the bridge-based methods, which considers the rating sparsity degrees of individual users in different domains.
- SSCDR is a semi-supervised bridge-based method.

Experiments

Research questions

- RQ1 Why we need an auxiliary domain and why we need to introduce CDR? How does PTUPCDR perform in extremely cold-start scenarios comparing to state-of-the-art models with a CDR perspective?
- RQ2 How does PTUPCDR perform in more practical scenarios of real-world recommendations?
- RQ3 Why could PTUPCDR perform better?

Dataset splits

- Three cross-domain tasks.
- Cold-start scenario.
- Warm-start scenario.
- Train: Test = 2:8 / 5:5/ 8:2

CDR Tasks	Domain		Item		User			Rating	
	Source	Target	Source	Target	Overlap	Source	Target	Source	Target
Task1	Movie	Music	50,052	64,443	18,031	123,960	75,258	1,697,533	1,097,592
Task2	Book	Movie	367,982	50,052	37,388	603,668	123,960	8,898,041	1,697,533
Task3	Book	Music	367,982	64,443	16,738	603,668	75,258	8,898,041	1,097,592

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Experiments

	β	Metric	TGT	CMF	DCDCSR	SSCDR	EMCDR	PTUPCDR	Improve
Task1	20%	MAE	4.4803	1.5209	1.4918	1.3017	1.2350	**1.1504***	6.86%
		RMSE	5.1580	2.0158	1.9210	1.6579	1.5515	**1.5195**	2.06%
	50%	MAE	4.4989	1.6893	1.8144	1.3762	1.3277	**1.2804***	3.57%
		RMSE	5.1736	2.2271	2.3439	1.7477	1.6644	**1.6380**	1.59%
	80%	MAE	4.5020	2.4186	2.7194	1.5046	1.5008	**1.4049***	6.39%
		RMSE	5.1891	3.0936	3.3065	1.9229	1.8771	**1.8234***	2.86%
Task2	20%	MAE	4.1831	1.3632	1.3971	1.2390	1.1162	**0.9970***	10.68%
		RMSE	4.7536	1.7918	1.7346	1.6526	1.4120	**1.3317***	5.69%
	50%	MAE	4.2288	1.5813	1.6731	1.2137	1.1832	**1.0894***	7.93%
		RMSE	4.7920	2.0886	2.0551	1.5602	1.4981	**1.4395***	3.91%
	80%	MAE	4.2123	2.1577	2.3618	1.3172	1.3156	**1.1999***	8.80%
		RMSE	4.8149	2.6777	2.7702	1.7024	1.6433	**1.5916***	3.15%
Task3	20%	MAE	4.4873	1.8284	1.8411	1.5414	1.3524	**1.2286***	9.15%
		RMSE	5.1672	2.3829	2.2955	1.9283	1.6737	**1.6085***	3.90%
	50%	MAE	4.5073	2.1282	2.1736	1.4739	1.4723	**1.3764***	6.51%
		RMSE	5.1727	2.7275	2.6771	1.8441	1.8000	**1.7447***	3.07%
	80%	MAE	4.5204	3.0130	3.1405	1.6414	1.7191	**1.5784***	3.84%
		RMSE	5.2308	3.6948	3.5842	2.1403	2.1119	**2.0510***	2.88%

Results (RQ1)

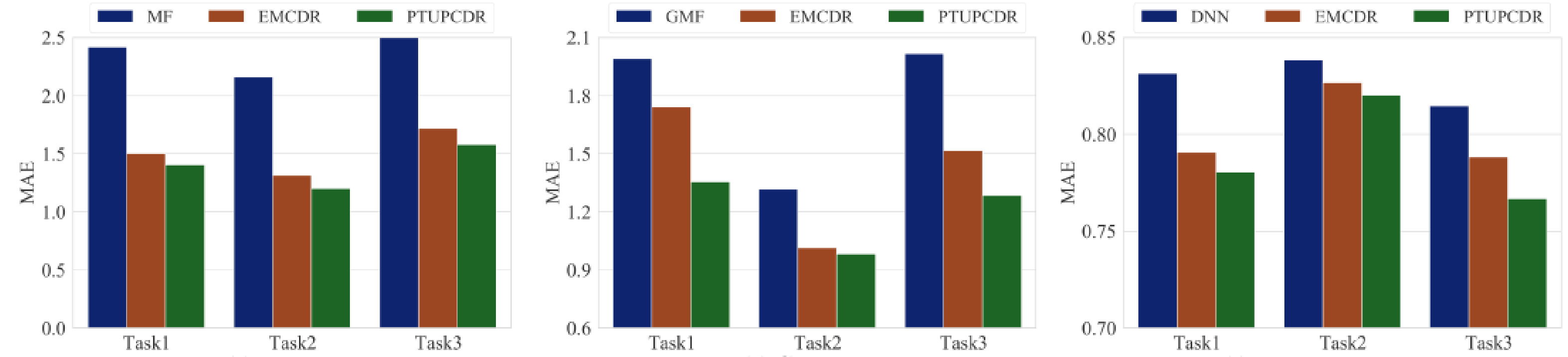
- Utilizing data from an auxiliary domain is an effective way to alleviate data sparsity and improve the recommendation performance in the target domain.
- It is essential to study CDR by using the auxiliary domain more effectively.
- PTUPCDR could outperform the best baseline significantly in most tasks.

Experiments

Generalization Experiments (RQ2)

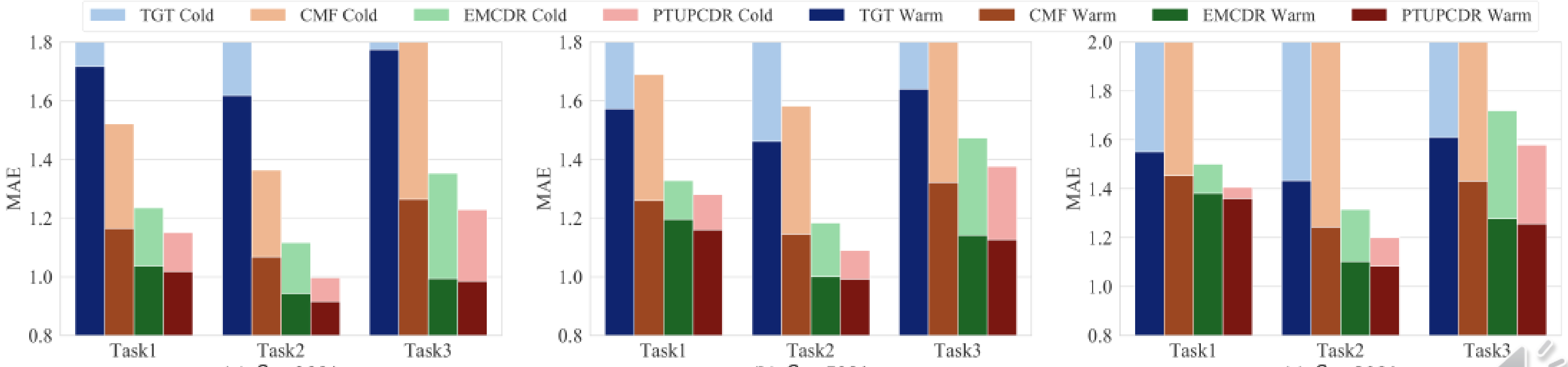
- PTUPCDR can be applied upon various base models.
- PTUPCDR can work well in both cold- and warm-start tasks.

More base structures



(a) MF Based (b) GMF Based (c) YouTube DNN Based

Warm-start task



(a) $\beta = 20\%$ (b) $\beta = 50\%$ (c) $\beta = 80\%$

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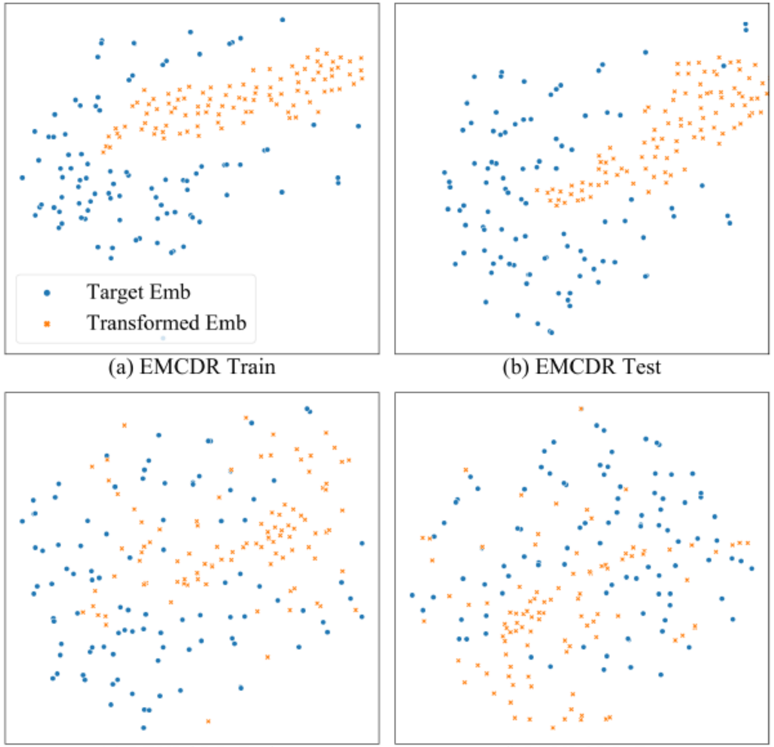
Experiments



(a) EMCDR Train (b) EMCDR Test

(c) PTUPCDR Train (d) PTUPCDR Test

Analysis Experiments (RQ3)

- The embeddings transformed by EMCDR are very concentrated.
- The transformed embeddings by PTUPCDR are scattered across the target domain feature space.
- PTUPCDR has a good personalization capacity.

Thanks Q & A

Name: Yongchun Zhu | Email: zhuyongchun18s@ict.ac.cn

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