Personalized Transfer of User Preferences for Cross-domain Recommendation

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Source : WSDM’ 22

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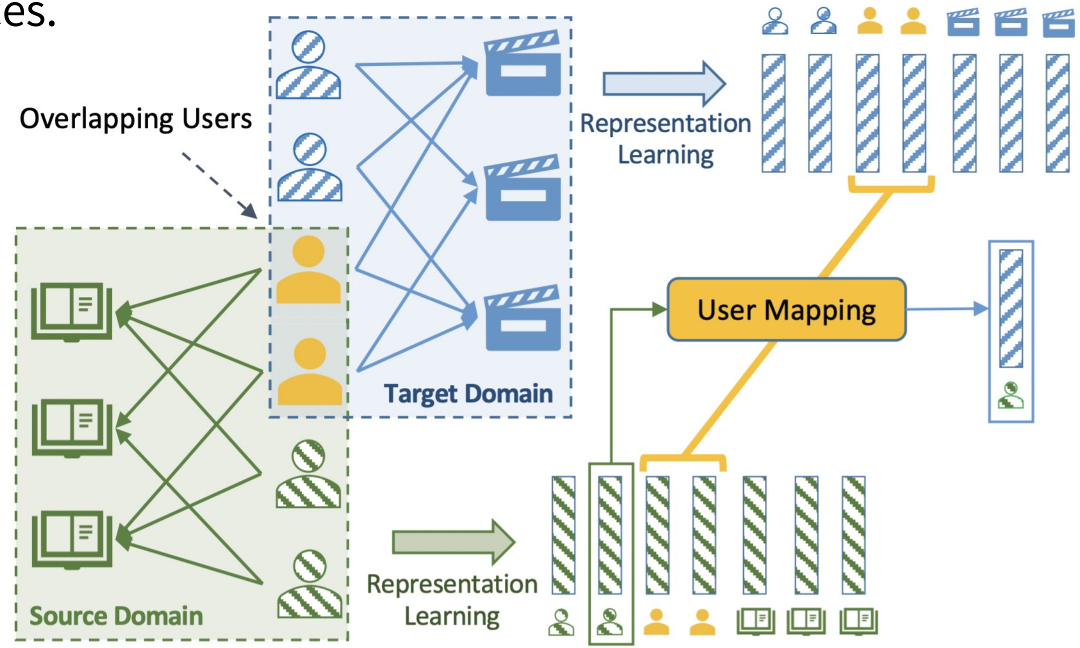
Outline

- **Introduction**
- Method
- Experiment
- Conclusion

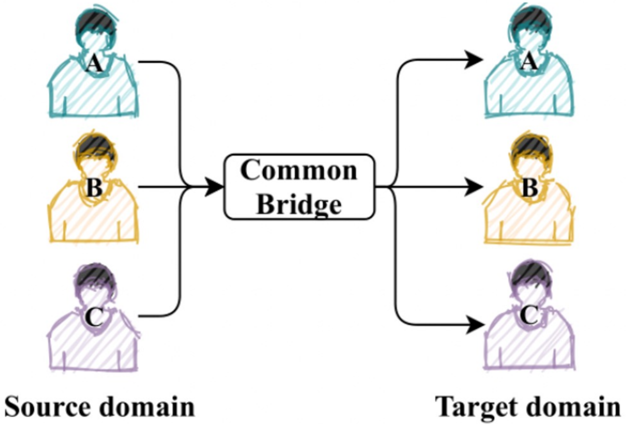
Introduction

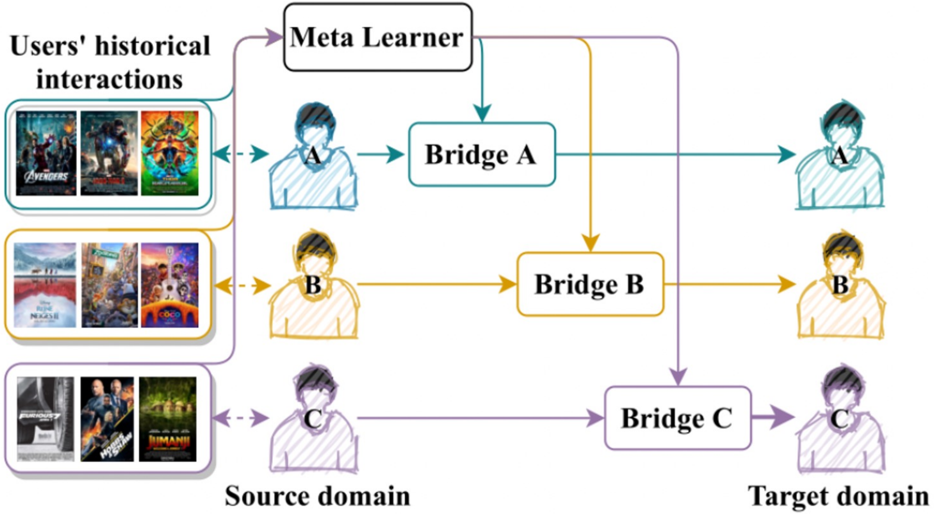
- Common bridge methods assume that all users share the same user preferences.



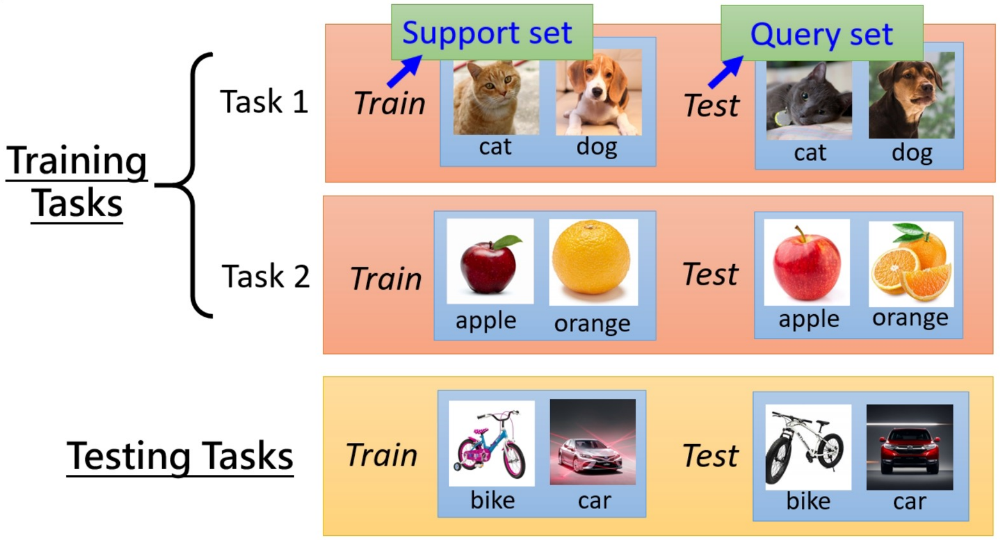
Introduction

- Past CDR methods share the common bridge function, this paper use personalized bridge function.





Meta Learning

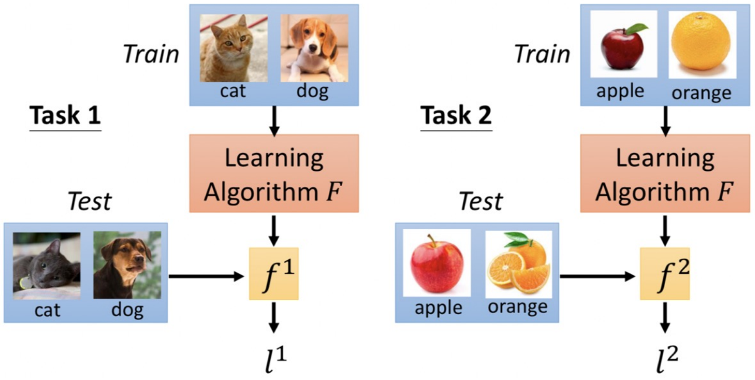


$$L(F) = \sum_{n=1}^{N} l^n$$

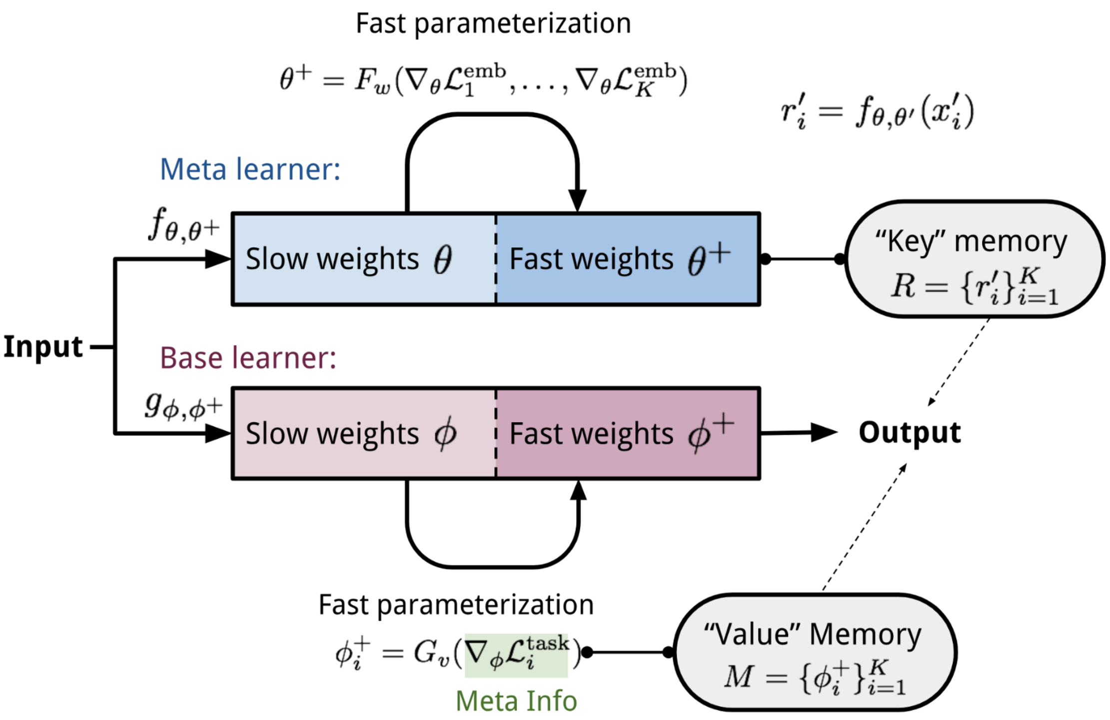
N tasks

Testing loss for task n after training

- Defining the goodness of a function F



Meta Network



Input:

- user $\mathcal{U} = \{u_1, u_2, \ldots\}$
  - $\mathcal{U}^s, \mathcal{U}^t, \mathcal{U}^o$ ($\mathcal{U}^o = \mathcal{U}^s \cap \mathcal{U}^t$)
- item $\mathcal{V} = \{v_1, v_2, \ldots\}$
  - $\mathcal{V}^s, \mathcal{V}^t$
- user's sequential interaction $\mathcal{S}_{u_i} = \{v^s_{t_1}, v^s_{t_2}, \cdots, v^s_{t_n}\}$

Output:

- rating $r_{ij} \in \mathcal{R}$, from user u_i and item v_j
  - $\mathcal{R}^s, \mathcal{R}^t$

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  - Personalized Bridge
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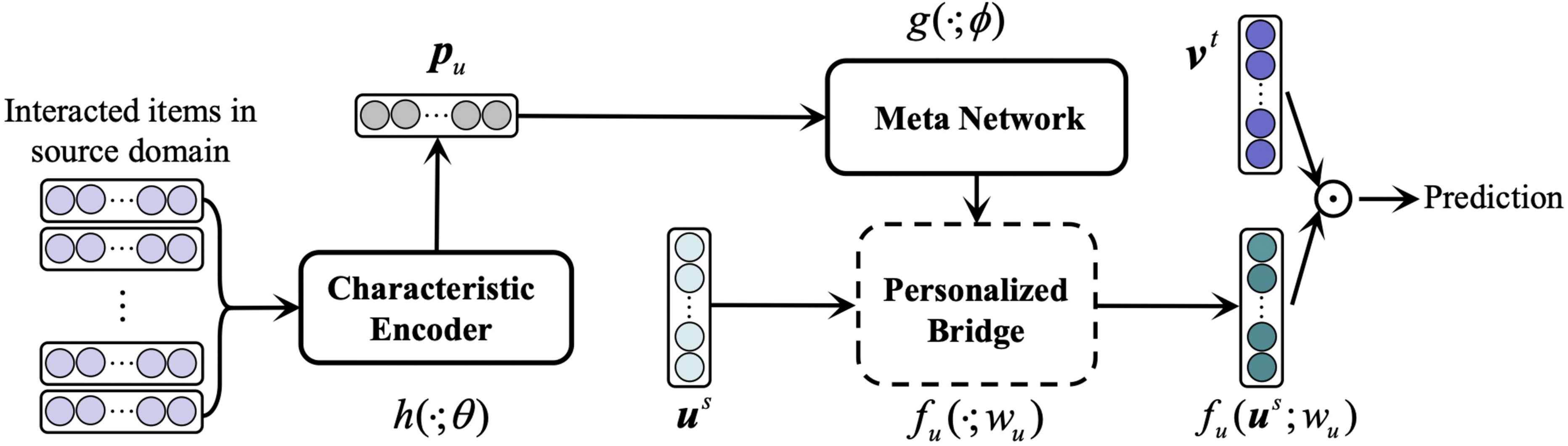
Method



Interacted items in source domain
Characteristic Encoder
$h(\cdot;\theta)$
$\boldsymbol{p}_u$
$g(\cdot;\phi)$
Meta Network
$\boldsymbol{u}^s$
Personalized Bridge
$f_u(\cdot;w_u)$
$\boldsymbol{v}^t$
$f_u(\boldsymbol{u}^s;w_u)$
Prediction

Characteristic Encoder

Transferable characteristic embedding of user

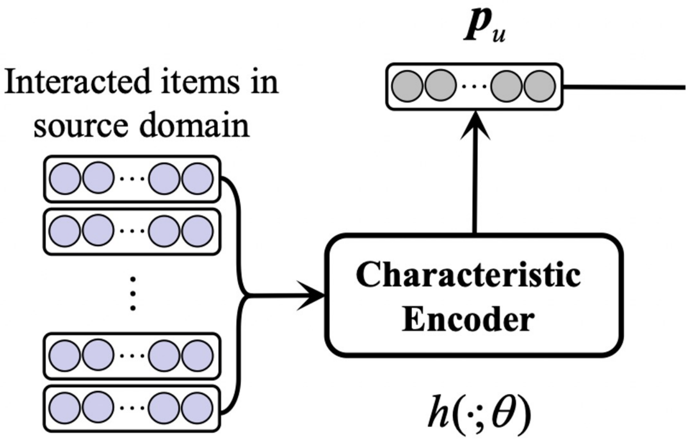
$$\boldsymbol{p}_{u_i} = \sum_{v_j^s \in \mathcal{S}_{u_i}} a_j \boldsymbol{v}_j^s,$$

input: $\mathcal{S}_{u_i} = \{v_{t_1}^s, v_{t_2}^s, \cdots, v_{t_n}^s\}$

Attention network

$$a'_j = h(\boldsymbol{v}_j; \theta),$$

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

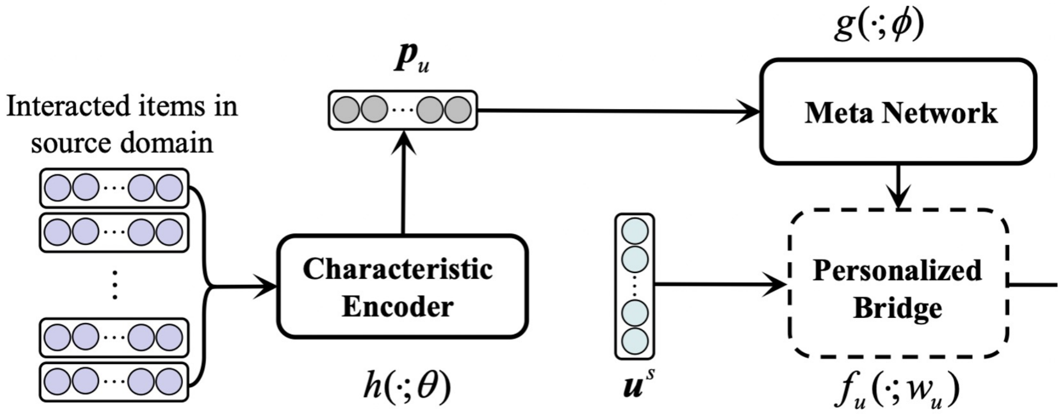


Personalized Bridge

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

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

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



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Experiment

- **Dataset**
  - Task1 : Movie -> Music
  - Task2 : Book -> Movie
  - Task3 : Book -> Music

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

Experiment

- **Evaluation**
  - Root Mean Squared Error(RMSE)
  - Mean Absolute Error(MAE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|$$

- **Baselines**
  - TGT : Target MF model.
  - CMF : Users' embedding are shared across the source and target domains.
  - EMCDR : Transfer users' embedding from source to target.
  - DCDCSR : Bridge-based methods. Considering the rating sparsity degrees.
  - SSCDR : Semi-supervised bridge-based method.

β : the proportion of test user of overlapping users

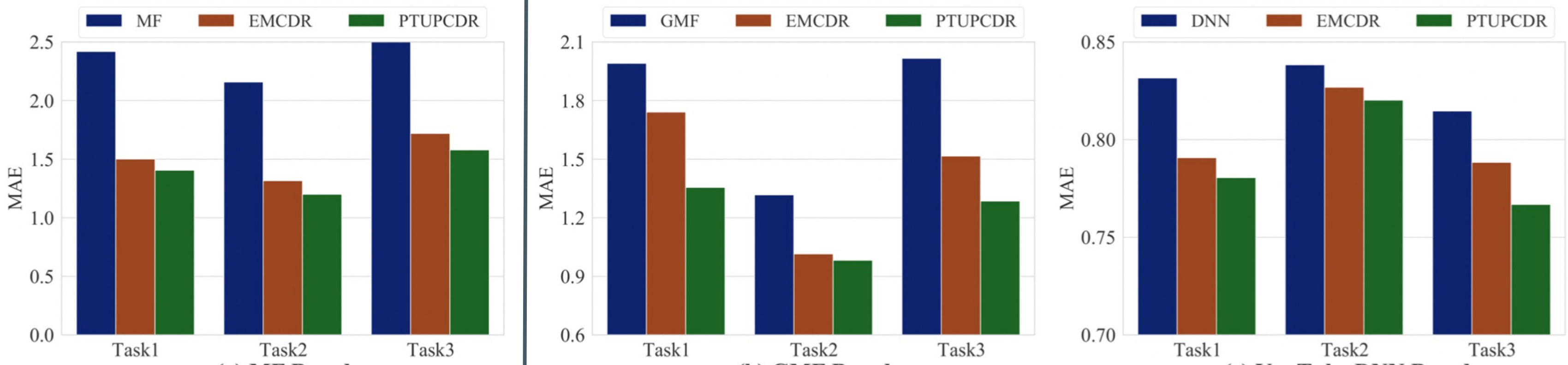
Experiment

	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%

Mean results over five random round

Experiment

- Non-neural based model v.s. Neural based model



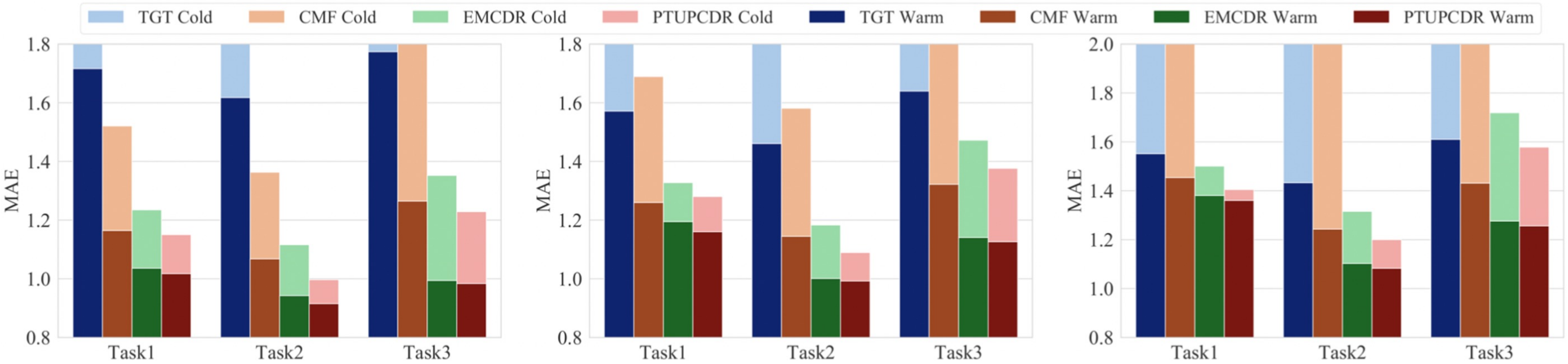
(a) MF Based **(b) GMF Based** **(c) YouTube DNN Based**

Non-neural

Neural

Experiment

- Warm-start v.s. Cold-start



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

Conclusion

- A single bridge function is hard to capture various relationships between user preferences in source and target.
- In cold-start problems, using personalized bridge functions could lead to better results.