Australian Artificial
Intelligence Institute

Federated Recommendation with Additive Personalization

Zhiwei Li[1], Guodong Long[1], Tianyi Zhou[2]

[1]Australian AI Institute, Faculty of Engineering and IT, University of Technology Sydney
[2]Department of Computer Science, University of Maryland, College Park

INTRODUCTION

- Federated Recommendation Systems (FedRecSyss) aim to protect user privacy and share knowledge across clients by keeping user data local while balancing the trade-off between communication costs and model precision.
- Current FedRecSyss ignore that <u>users have different preference to each item and they may focus on different attributes of the item.</u>
- This work follows **Horizontal Federated Learning (FL) assumption** [1]: each user has a **distinct** embedding and **<u>unique</u>** dataset, yet the items are **<u>shared</u>** among all users.

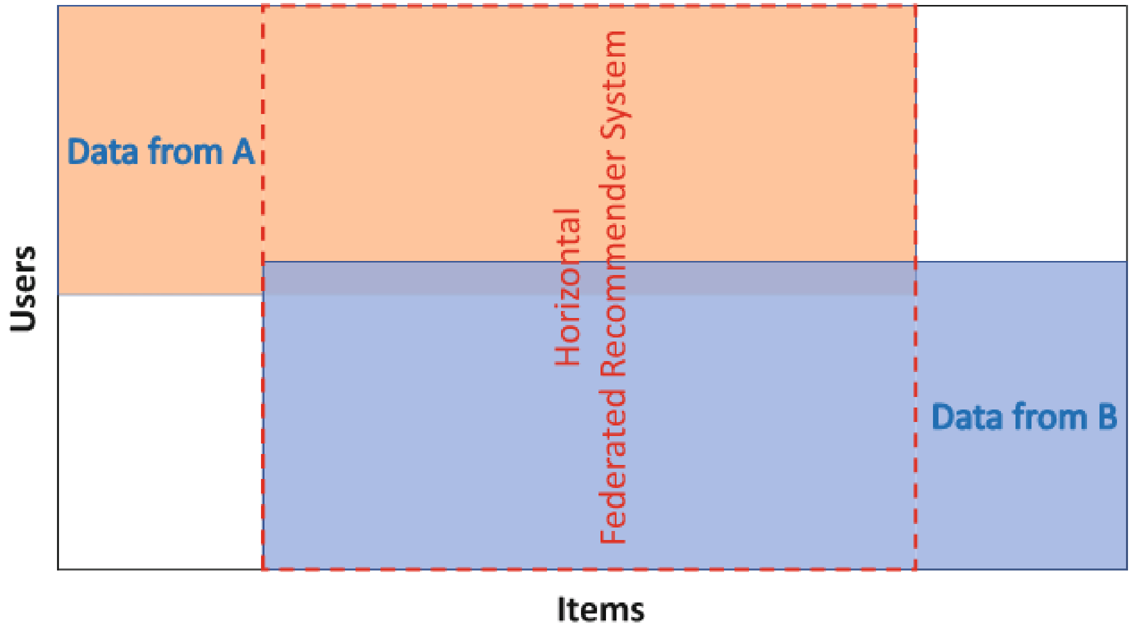

Fig. 1. Horizontal FL Assumption.

[1] Zareen Alamgir, Farwa K Khan, and Saira Karim. Federated recommenders: methods, challenges and future. Cluster Computing, 25(6):4075–4096, 2022.

FedRAP

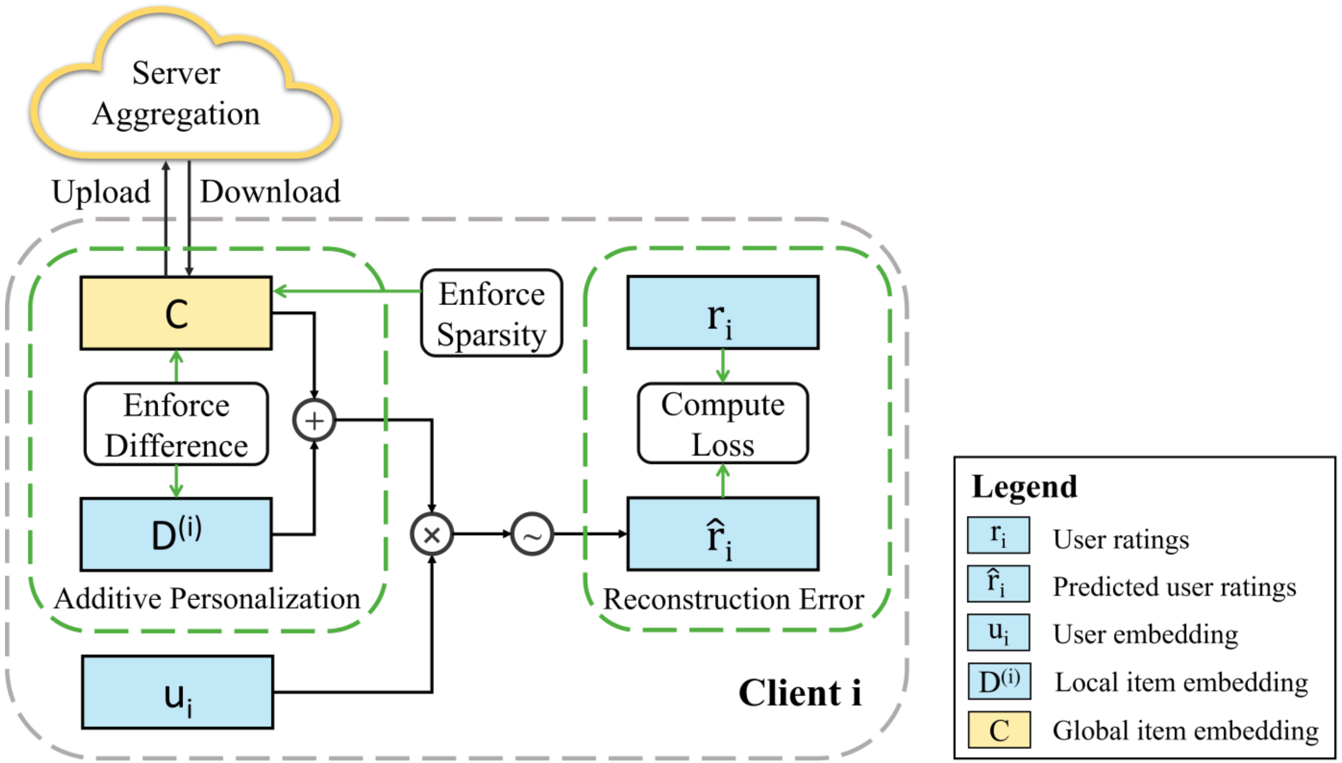

Fig. 2 The framework of FedRAP.

Based on the idea that users' unique preferences, informed by both personal and item information, drive their ratings, we propose a novel **Fed**erated **R**ecommendation system with **A**dditive **P**ersonalization (**FedRAP**).

FedRAP aims to use this partial data to recommend unexplored items to users.

FedRAP – Two-Way Personalization

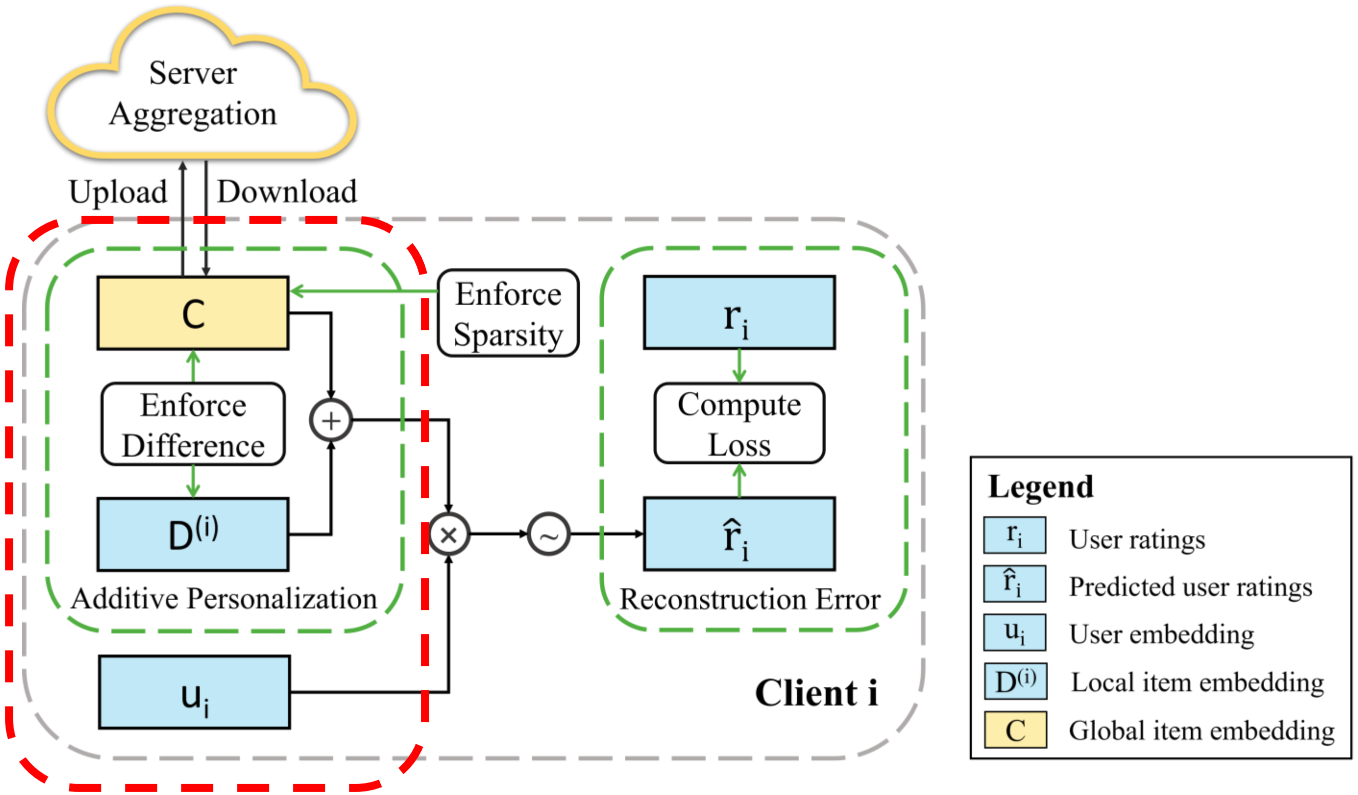

Fig. 2 The framework of FedRAP.

$$\min_{\mathbf{U},\mathbf{C},\mathbf{D}^{(i)}} \sum_{(i,j)\in\mathbf{\Omega}} -(r_{ij}\log \hat{r}_{ij} + (1-r_{ij})\log(1-\hat{r}_{ij})).$$

where $\hat{r}_{ij} = 1/(1+e^{-<\mathbf{u_i},(\mathbf{D^{(i)}}+\mathbf{C})_j>})$

Two-way Personalization: FedRAP delivers private user embeddings for each client while achieving Additive Personalization for items by summing user-related local item embeddings with globally aggregated item embeddings updated on the server.

FedRAP – Dual Regularizers

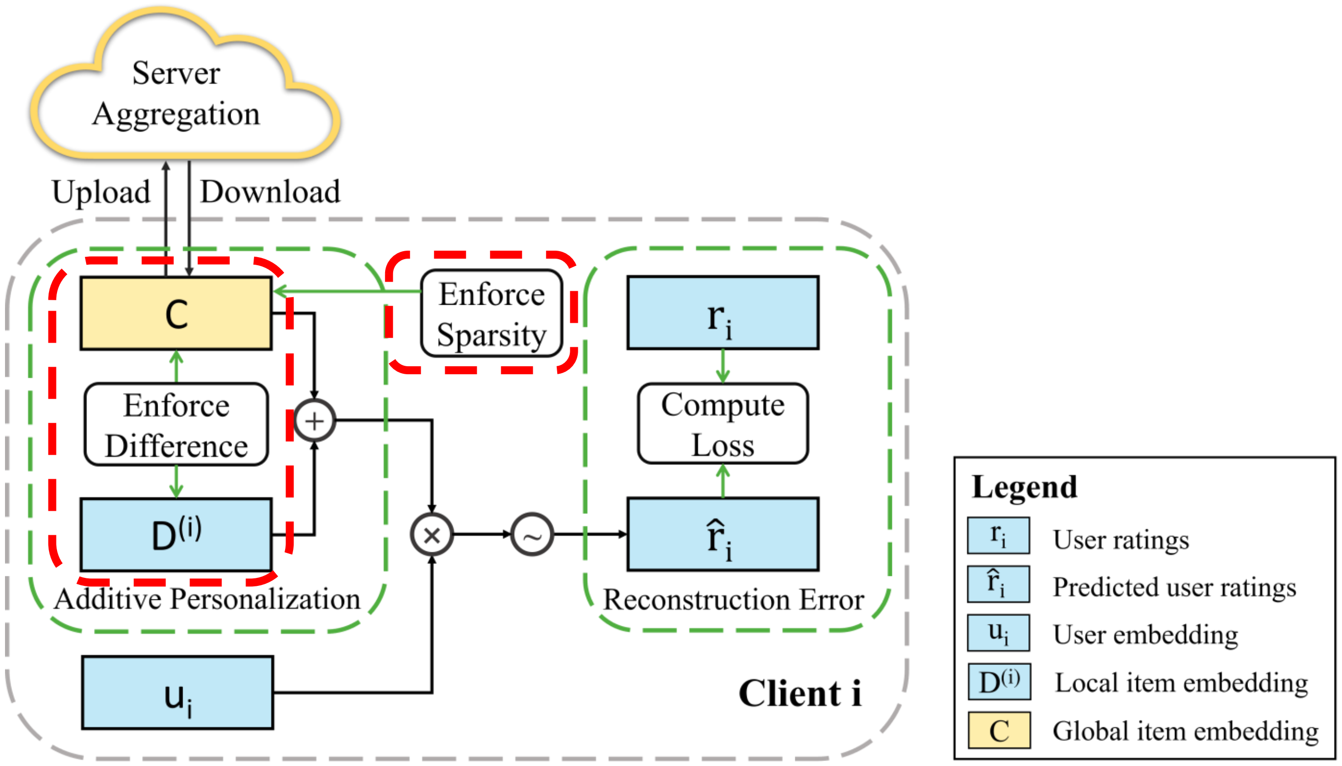

Fig. 2. The framework of FedRAP.

$$\min_{\mathbf{U},\mathbf{C},\mathbf{D}^{(i)}} \sum_{(i,j)\in\mathbf{\Omega}} -(r_{ij}\log\hat{r}_{ij} + (1-r_{ij})\log(1-\hat{r}_{ij})).$$

where $\hat{r}_{ij} = 1/(1+e^{-<\mathbf{u_i},(\mathbf{D^{(i)}}+\mathbf{C})_j>})$

Enforce Sparsity: $\min_{\mathbf{C}} ||\mathbf{C}||_1$

Enforce Difference: $\max_{\mathbf{C},\mathbf{D}^{(i)}} \sum_{i=1}^{n} ||\mathbf{D}^{(i)} - \mathbf{C}||_F^2.$

Dual Regularizers: FedRAP promotes a sparse global item embedding to cut down on communication costs and overhead, while also ensuring a difference between the global and local item embeddings to complement each other.

FedRAP – Varying regularization weights

$$\min_{\mathbf{U},\mathbf{C},\mathbf{D}^{(i)}} \sum_{i=1}^{n} \left(\sum_{(i,j)\in\mathbf{\Omega}} -\left(r_{ij}\log \hat{r}_{ij} + (1-r_{ij})\log(1-\hat{r}_{ij})\right) - \boxed{\lambda_{(a,v_1)}} \|\mathbf{D}^{(i)} - \mathbf{C}\|_F^2 \right) + \boxed{\mu_{(a,v_2)}} \|\mathbf{C}\|_1,$$

$$\text{where } \hat{r}_{ij} = 1/\left(1+e^{-<\mathbf{u_i},(\mathbf{D^{(i)}}+\mathbf{C})_j>}\right)$$

In this work, we set $\lambda_{(a,v_1)} = \tanh\left(\frac{a}{10}\right) * v_1$, and $\mu_{(a,v_2)} = \tanh\left(\frac{a}{10}\right) * v_2$

Varying regularization weights: To mitigate the potential performance loss due to additive personalization in the early training stages, FedRAP employs a strategy of incrementally increasing regularization weights. This method smoothly transitions from fully personalized to additive personalization.

FedRAP – Objective

$$\min_{\mathbf{U},\mathbf{C},\mathbf{D}^{(i)}} \sum_{i=1}^{n}\left(\sum_{(i,j)\in\mathbf{\Omega}} -(r_{ij}\log\hat{r}_{ij}+(1-r_{ij})\log(1-\hat{r}_{ij}))-\lambda_{(a,v_1)}\|\mathbf{D}^{(i)}-\mathbf{C}\|_F^2\right)+\mu_{(a,v_2)}\|\mathbf{C}\|_1,$$

$$\text{where } \hat{r}_{ij}=1/(1+e^{-<\mathbf{u_i},(\mathbf{D^{(i)}}+\mathbf{C})_j>})$$

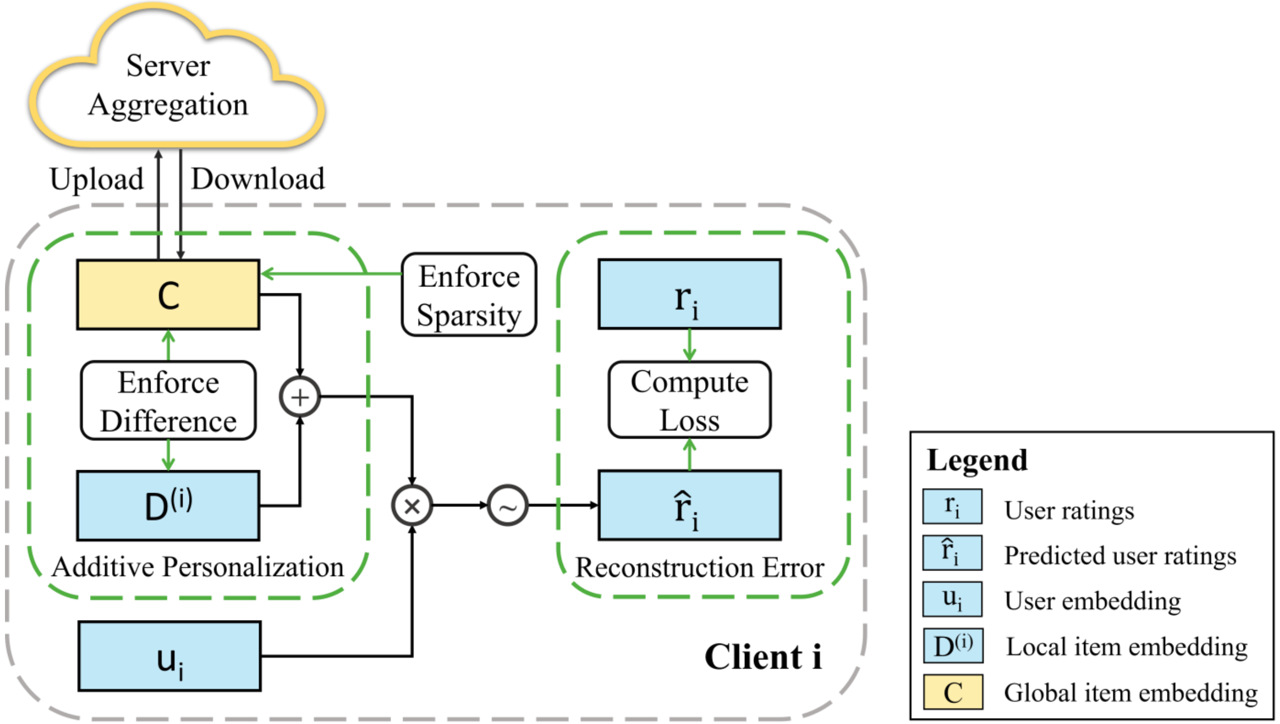

Fig. 2. The framework of FedRAP.

Experiments – Datasets & Main Results

Table 1. The statistic information of the datasets used in the research.

Datasets	#Ratings	#Users	#Items	Sparsity
TaFeng	100,000	120	32,266	78.88%
ML-100k	100,000	943	1,682	93.70%
ML-1M	1,000,209	6,040	3,706	95.53%
Video	23,181	1,372	7,957	99.79%
LastFM	92,780	1,874	17,612	99.72%
QB-article	266,356	24,516	7,455	99.81%

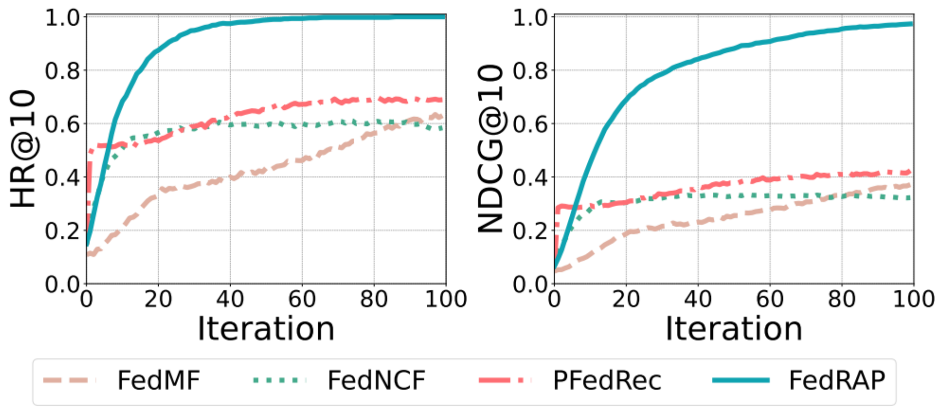

Fig. 3. Convergence and efficiency comparison of four methods on the ML-100K dataset.

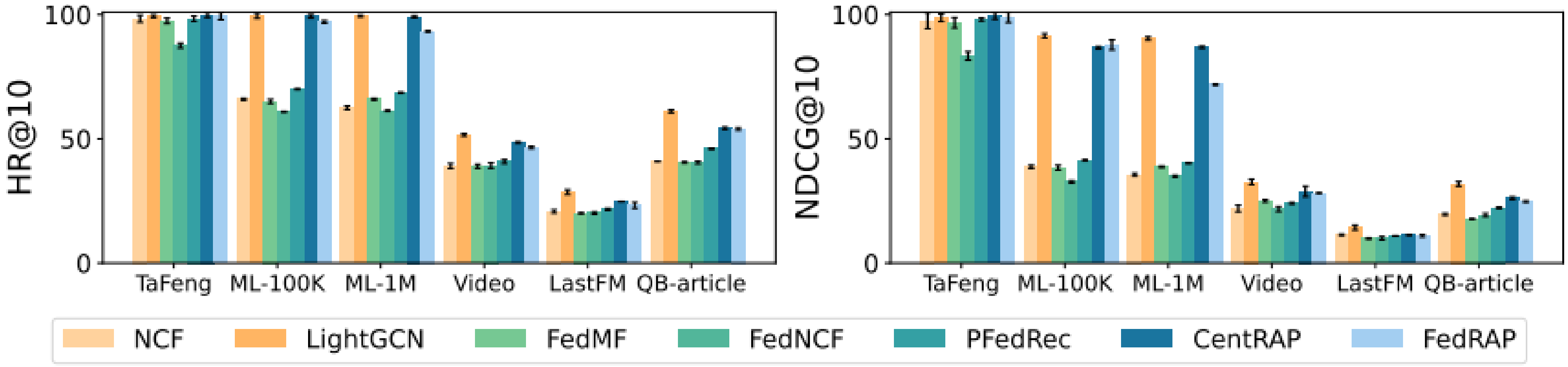

Fig. 4 Evaluation metrics (%) on six real-world recommendation datasets.

Experiments – Ablation Study on Item Personalization

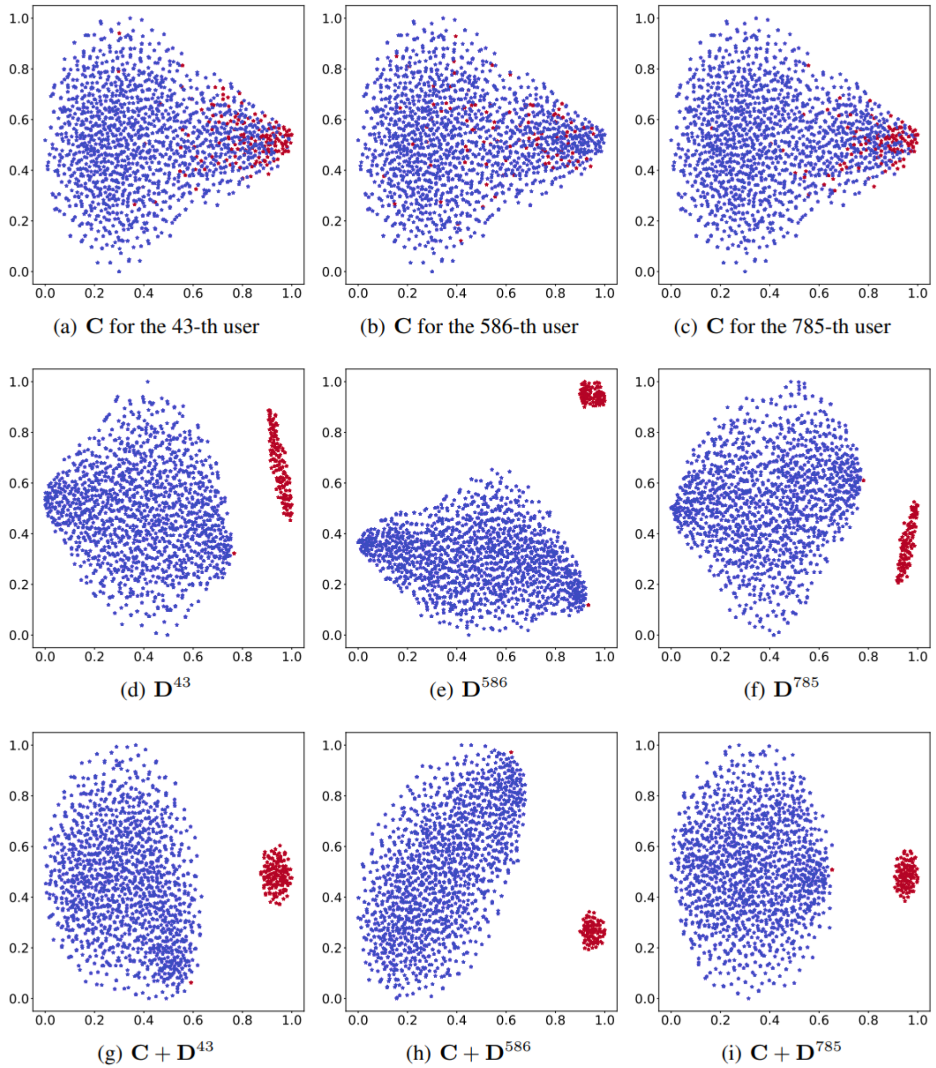

Fig. 5. t-SNE visualization of item embeddings learnd by FedRAP.

Conclusion

- FedRAP provides a novel federated recommendation model that achieves both user and item personalization, transitioning from full to additive personalization with enhanced efficiency and privacy.
- The model's effectiveness is validated on six datasets, indicating its applicability to various federated learning contexts, although it acknowledges the challenge of item embedding storage, with future solutions in development.

Thank You!

Paper

Code

Acknowledgment

This research was supported partially by the Australian Government through the Australian Research Council's Discovery Projects funding scheme (project DP220100768). The views expressed herein are those of the authors and are not necessarily those of the Australian Government or Australian Research Council.