PREFER: Point-of-interest REcommendation with efficiency and privacy-preservation via Federated Edge leaRning

Yeting Guo, Zhiping Cai, Hui Zeng, Tongqing Zhou, Nong Xiao:

National University of Defense Technology, China

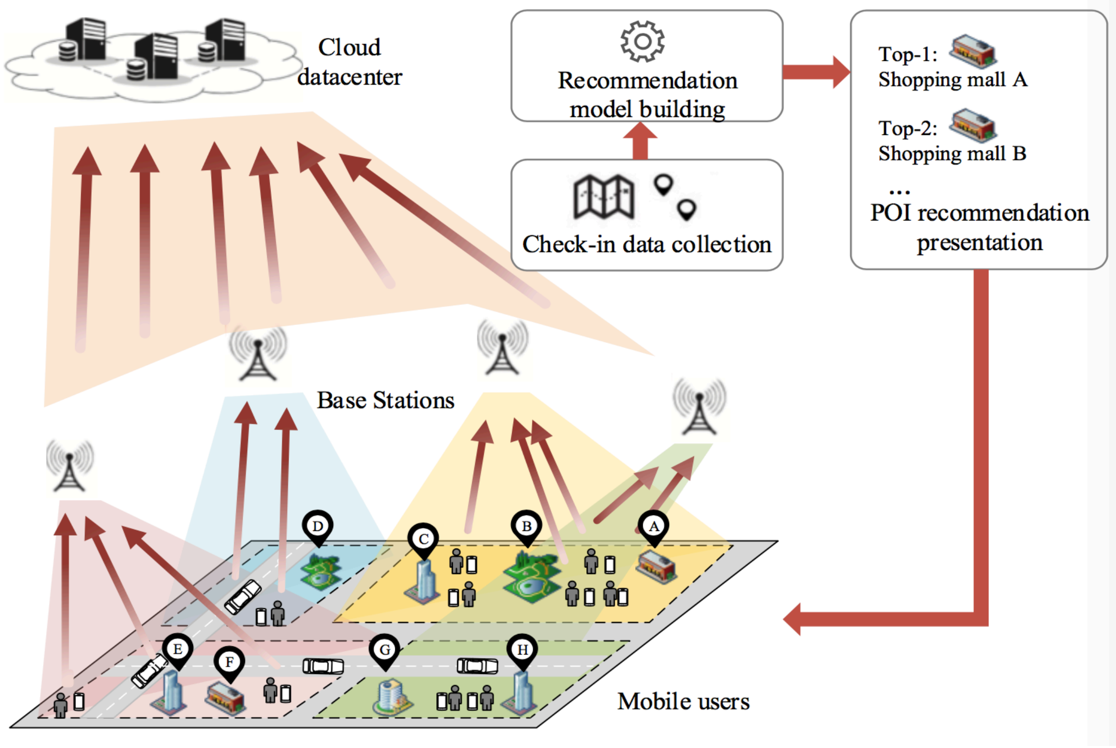
Fang Liu: Hunan University, China

Li Chen: University of Louisiana at Lafayette, USA

Point-of-interest Recommendation

- One of the major tasks in location-based social networks, such as Foursquare, Gowalla and Wechat
- Explore new places (e.g. restaurants) for users, find target customers for advertising

Check-in activity



POI recommendation procedure

Problems

Data exposure

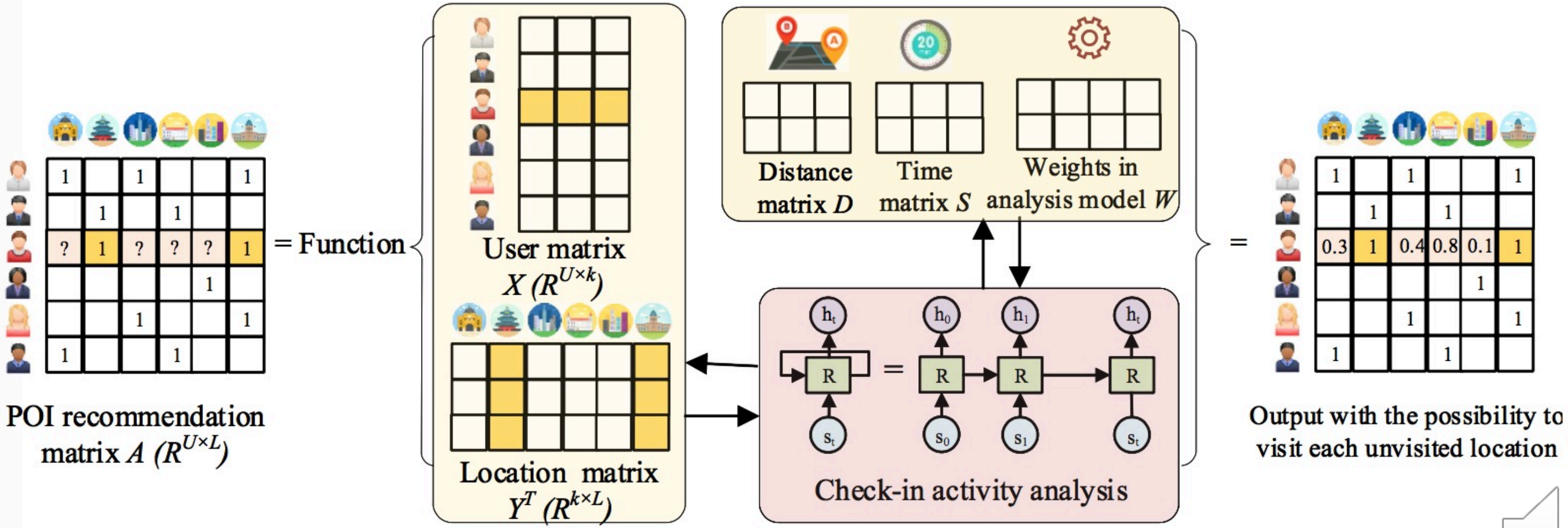
Criminals and stalkers spot and track victims with the help of check-in data.

Inefficiency

- Heavily dependent on network quality
- High carbon footprint and energy cost

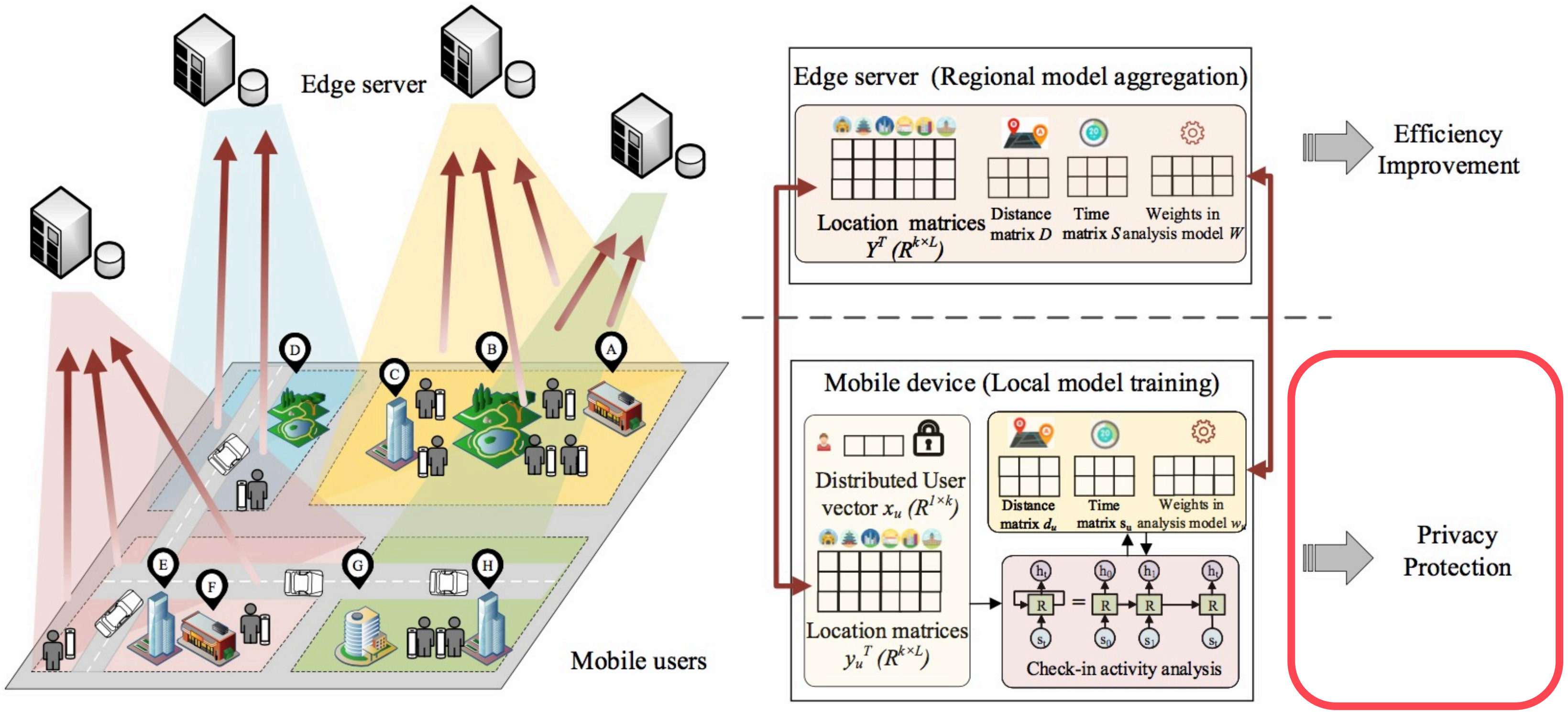
Incompatibility

Multi-dimensional factors are introduced into recommendation model.



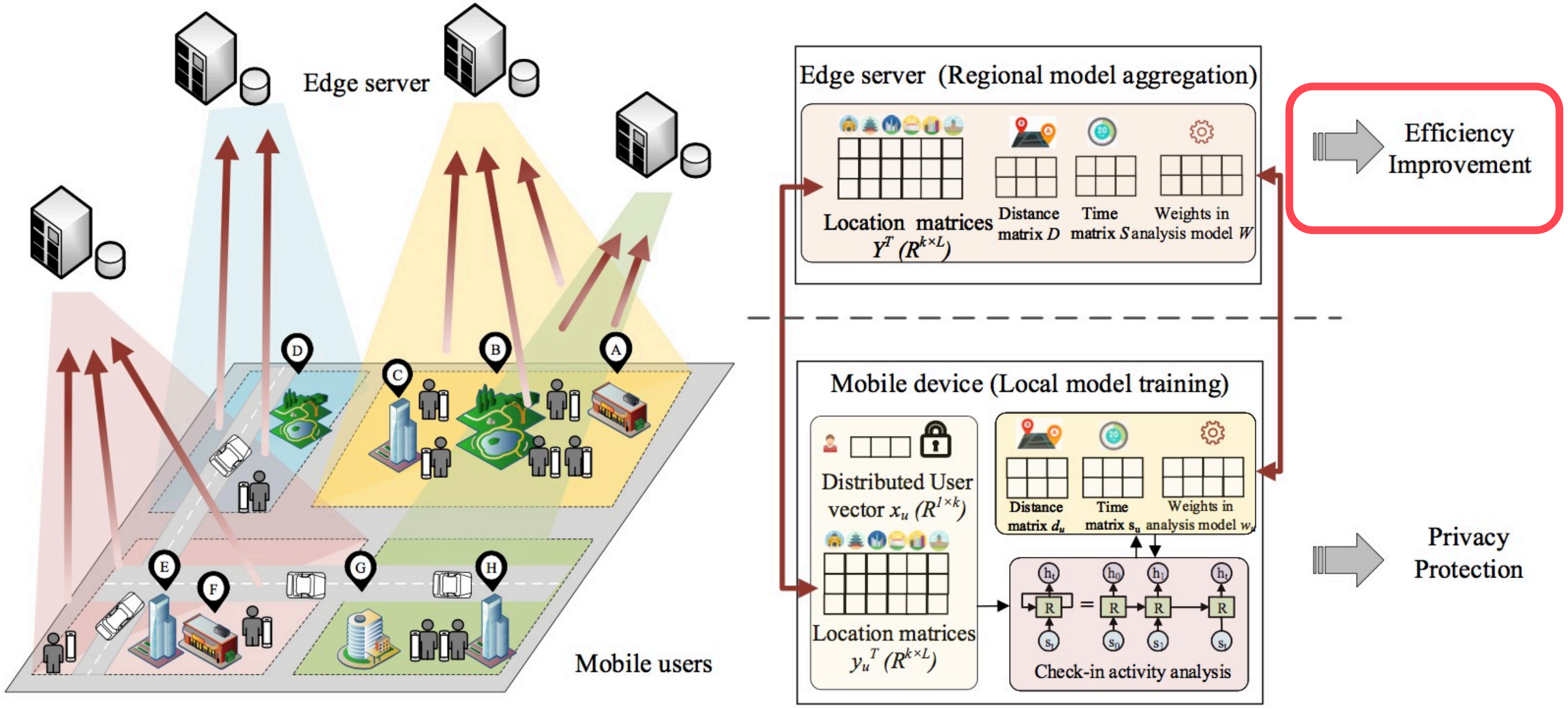
Our Solutions: PREFER

- **Q1:** Sensitive check-ins expose user privacy
- **A1:** Step 1: Train the local model with keeping sensitive data at local
  Step 2: Extract the non-sensitive multi-dimensional model features
  Step 3: Share features in replace of raw data to build a strong model



Our Solutions: PREFER

- ❑ **Q2:** High transmission delay from terminals to the cloud
- ❑ **A2：** Step 1: Edge servers collect decentralized model features
  Step 2: Update global model according to federated average algorithm
  Step 3: Inform terminals to train on the basis of the latest global model



Case Studies

- **PRME-G (Feng et al. 2015 IJCAI)**

Considering sequential information, individual preference, and geographical influence through variables X, Y and S.

$$D^S_{l_i,l_j} = \|s_{l_i} - s_{l_j}\|^2, \quad D^P_{u,l} = \|x_u - y_l\|^2$$

$$D^G_{u,l_i,l_j} = \begin{cases} D^P_{u,l_j} & if \;\; \Delta(l_i,l_j) > \tau \\ (1 + d_{l_i,l_j})^{0.25} \cdot (\alpha D^P_{u,l_j} + (1-\alpha) D^S_{l_i,l_j}) & otherwise \end{cases}$$

$$\Theta^* = argmin_\Theta \sum_{l_c \in L} \sum_{l_i \in L} \sum_{l_j \in L} (-ln\sigma(D^G_{u,l_c,l_i} - D^G_{u,l_c,l_j})) + \lambda\|\Theta\|^2$$

- **Distance2Pre (Cui et al. 2019 PAKDD)**

Introducing sequential and spatial factors into the POI recommendation model by RNN method.

$$x^t_u = f(U'[y^t_l; d^t_l], W' x^{t-1}_u, b)$$

$$s^t = SoftReLU(V_s x^t_u + b_s)$$

$$\widehat{x}^t_{ul} = (x^t_u)^T y^{t+1}_l + w_d s^t (d^{t+1}_p)$$

$$\Theta^* = argmin_\Theta \sum_{t=1}^{t=|S_u|} (-ln\sigma(\widehat{x}^t_{ul} - \widehat{x}^t_{ul'})) + \frac{\lambda}{2}\|\Theta\|^2$$

Evaluation

- **Experimental Platform**

Configuration	Entities		
	Mobile End Device	Edge Server	Cloud
CPU	8*Snapdragon 660@2.2GHZ	4*Intel(R)Core(TM) i5-4590 CPU@3.30GHZ	20*Intel(R) Xeon(R) CPU E5-2660 v3@2.60GHz
Memory	4GB	8GB	62GB
System	Android 7.1	Windows 10	Ubuntu 16.04

- **Dataset and Model**

Dataset	Region ID	User#	Location#	Record#	Sparsity	The number of trainable model parameters	
						PRME-G	Distance2Pre
Foursquare	1	1883	2589	138466	0.9716	155400	90557
	2	886	2582	64679	0.9717	154980	90340
	3	1048	2583	71614	0.9735	155040	90371
	4	728	2556	55695	0.9719	153420	89534
Gowalla	1	2065	2550	111289	0.9789	153060	99505
	2	484	2080	19686	0.9804	124860	84965
	3	837	2327	32990	0.9831	139680	92622

Evaluation

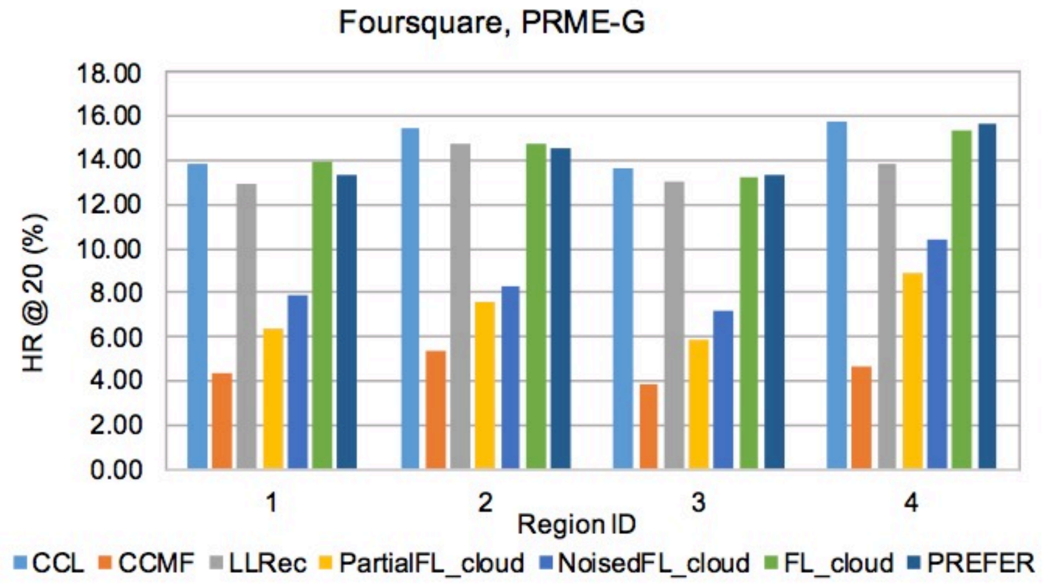
- **Metrics**
  - For recommendation quality, HR@20 (Hit Ratio) and NDCG@20 (Normalized Discounted cumulative gain)
  - For recommendation efficiency, t_{train_end}, t_{trans_edge}, t_{aggre_edge}, …
- **Baselines**

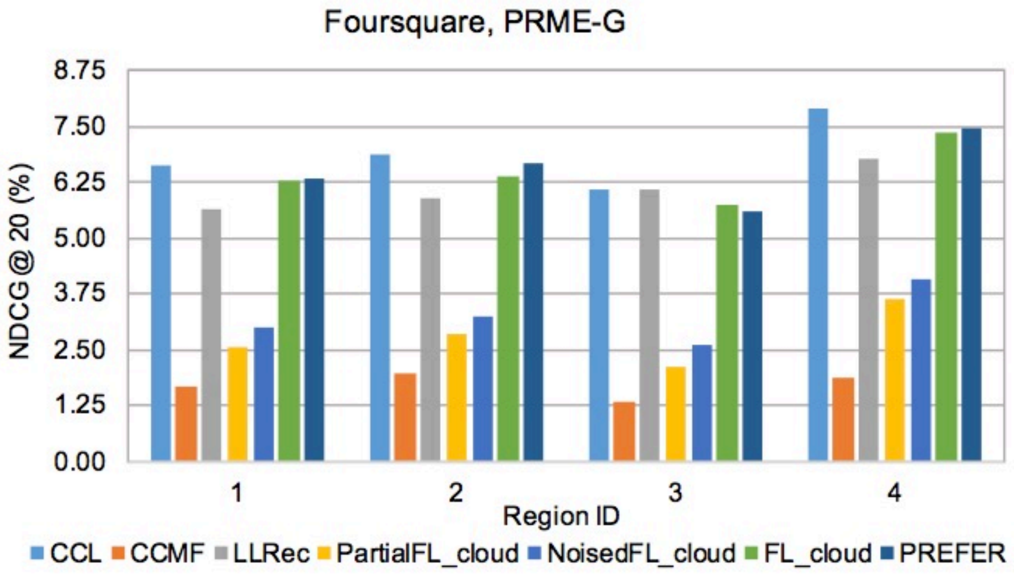
	CCL	CCMF	LLRec	PartialFL_cloud	NoisedFL_cloud	FL_cloud	PREFER
Where to train	cloud	cloud	end (student)& cloud (teacher)	end	end	end	end
What to train	user data	target domain data + noised auxiliary domain data	public user data (cloud) + private user data(end)	user data	user data	user data	user data
Where to aggregate	/	/	/	cloud	cloud	cloud	edge
What to aggregate	/	/	/	location matrix	noised user vector + noised location matrix	location matrix + time&distance -related matrices + model weights	location matrix + time&distance -related matrices + model weights

Evaluation

- **Results**

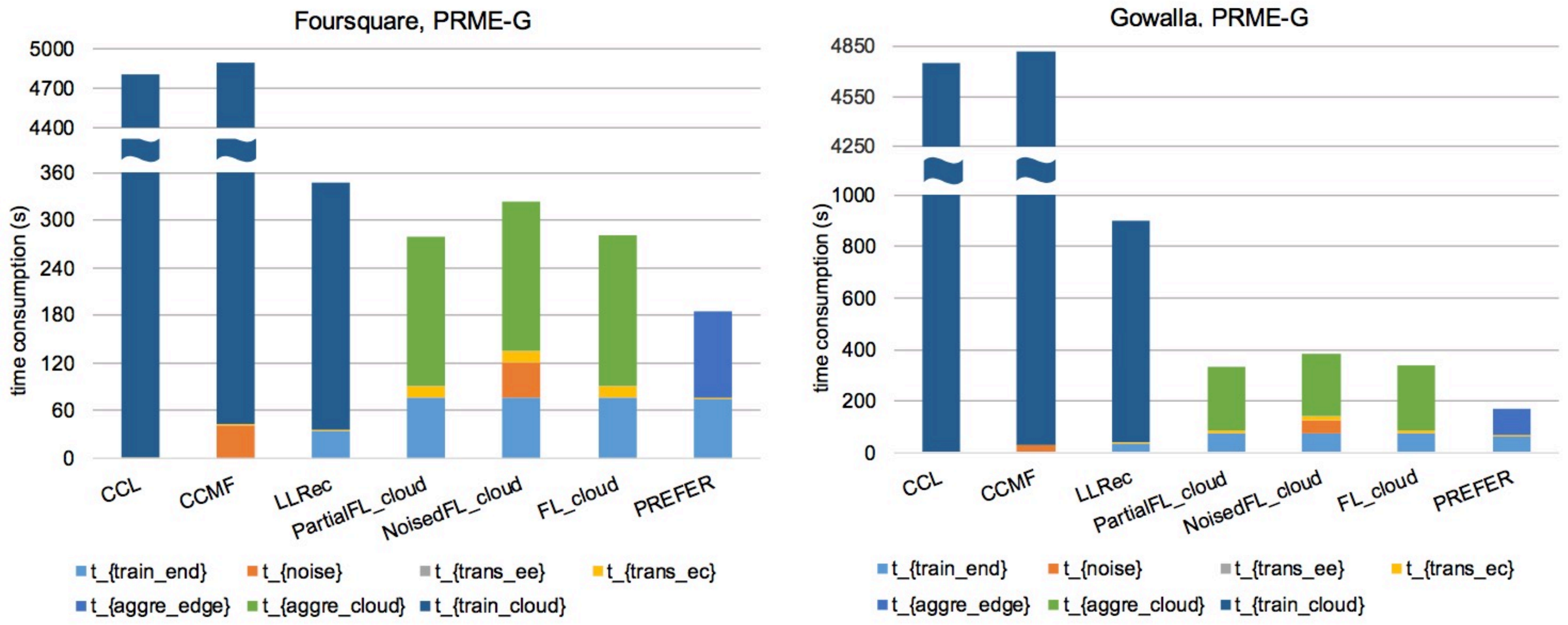
- Quality Comparison
  - PREFER strengthens user privacy protection with a little and acceptable sacrifice of quality.
  - PREFER achieves the highest recommendation quality among these privacy-preserving frameworks.
  - PREFER performs near the same quality with the baseline that aggregates in the cloud.





Evaluation

- Efficiency Comparison
  - PREFER significantly reduces the overall time consumption of recommendations.
  - PREFER also shows better recommendation efficiency than unidirectional teacher-student mode.
  - PREFER shortens the time consumption on parameter transmission and aggregation with the benefit of the edge server.

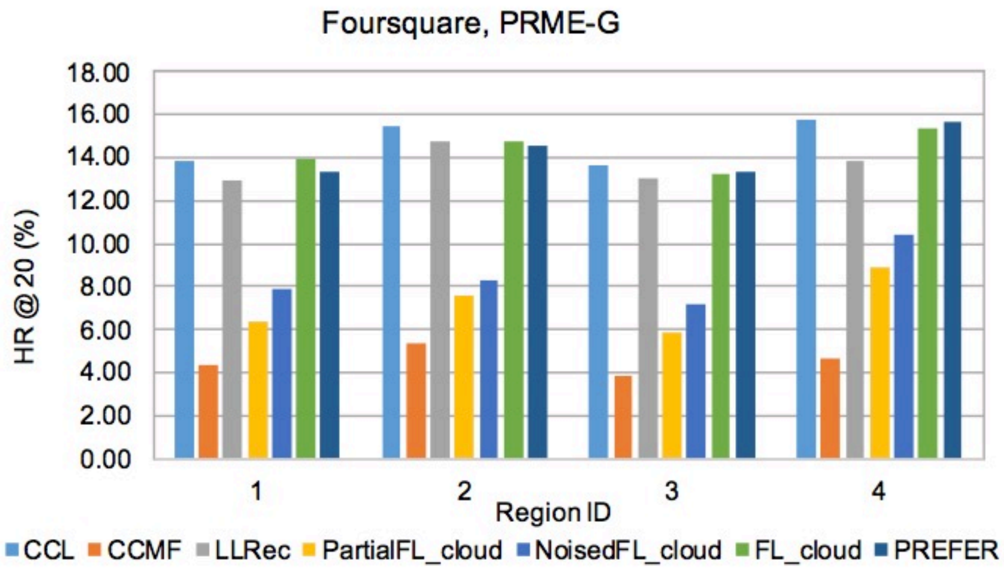


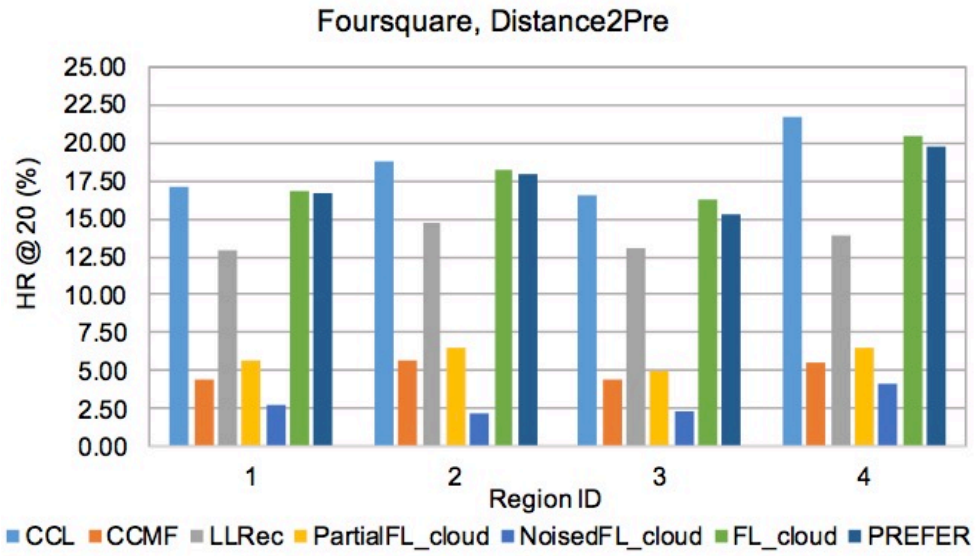
Evaluation

- **Results**

■ Compatibility Analysis

  ■ PREFER is more compatible with the mature and complex recommendation model.





Thank You!

- Questions ?

Yeting Guo

College of Computer, National University of Defense Technology

Email：guoyeting13@nudt.edu.cn