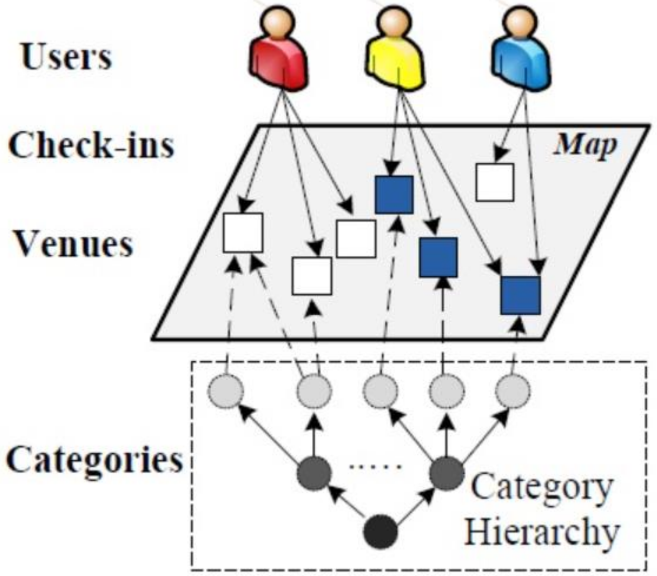
- Overview of multidomain recommender systems (Liang Hu, 25 mins)
- Multi-item domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-user domain recommender systems (Qi Zhang, 20 mins)
- Multi-data domain recommender systems (Z. Y. Lai, 20 mins)
- **Multi-spatial domain recommender systems (Qi Zhang 20 mins)**
- Multi-temporal domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-goal domain recommender systems (Liang Hu, 20 mins)
- Summary (Liang Hu, 5 mins)

Multi-spatial domain recommender systems

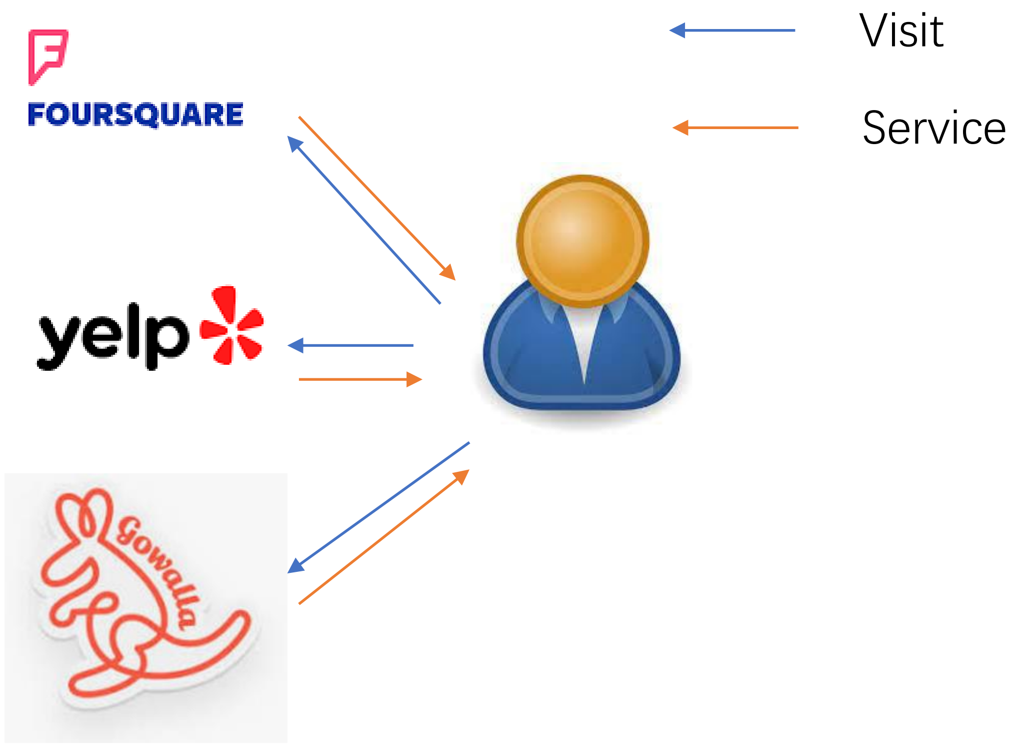
- Preliminary of multi-spatial domain recommender systems
- Multi-geographic point modeling for location-based recommendation
- Multi-system/sites modeling for multidomain recommendation

Spatial information surround us

- Spatial information is the digital connection between location, people and activities.



Location-based social networks



Multi-spatial domain recommender systems

- Multi-spatial domain RSs aims to leverage multiple spatial records of users to provide location-based services or integrate the records to improve recommendation accuracy.

- This results in two kinds of task:
  - Multi-geographic point modeling for location-based recommendation
  - Multi-system/sites modeling for recommendation

Multi-spatial domain recommender systems

- Preliminary of multi-spatial domain recommender systems
- Multi-geographic point modeling for location-based recommendation
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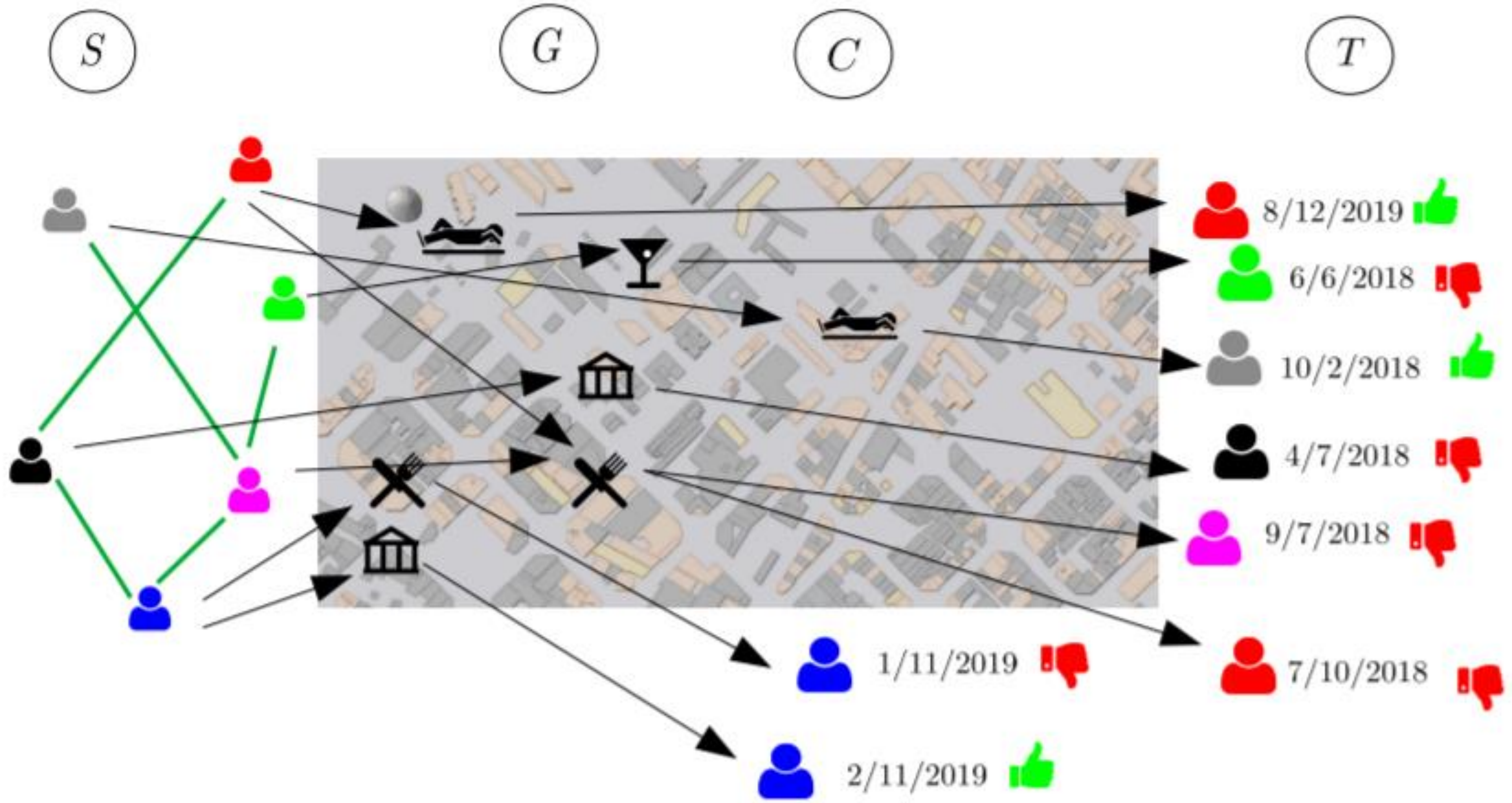
Point of Interest recommendation

A POI recommendation essentially exploits users' historical check-ins and other multi-modal information such as POI attributes and friendship network, to recommend POIs suitable for a user

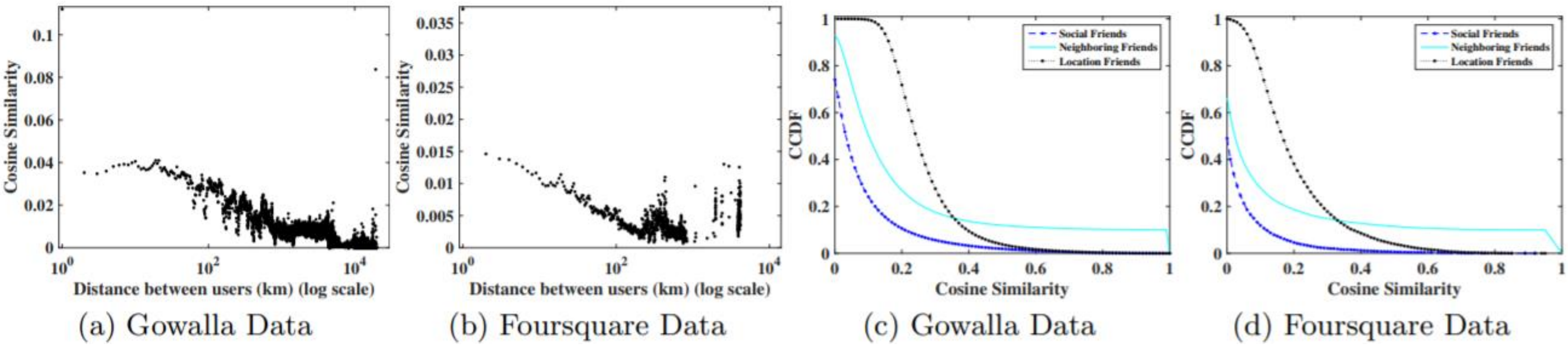


POI data sets

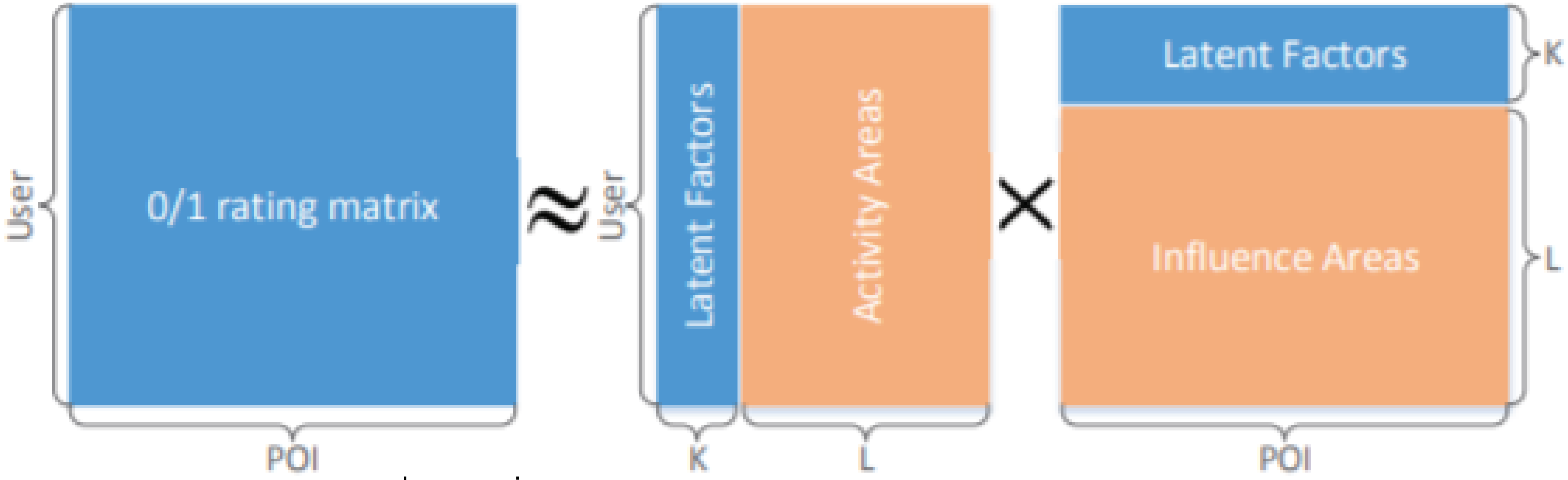
Details				Statistics				Evaluation Details	
Year	Ref.	Acronym	Cit.	Dataset	Users	POIs	Check-ins	Metrics used	Type of Split
2011	[159]	USG	784	Foursquare	153,577	96,229	N.A.	P, R	Random Per User
2011	[159]	USG	784	Whrrl	5,892	53,432	N.A.	P, R	Random Per User
2012	[8]	(N.A.)	477	Foursquare (NY)	2,886	N.A.	10,687	P, R	Other
2012	[8]	(N.A.)	477	Foursquare (LA)	228	N.A.	9,836	P, R	Other
2013	[167]	UTE, SE, UTE+SE	535	Foursquare	2,321	5,596	194,108	P, R	Random Per User
2013	[167]	UTE, SE, UTE+SE	535	Gowalla	10,162	24,250	456,988	P, R	Random Per User
2014	[85]	GeoMF	377	Jiepang	276,450	574,095	N.A.	P, R	Random Per User
2015	[80]	RankGeoFM	220	Foursquare	2,321	5,596	194,108	P, R	Temporal Per User
2015	[80]	RankGeoFM	220	Gowalla	10,162	24,250	456,988	P, R	Temporal Per User
2016	[148]	GE	184	Foursquare	114,508	62,462	1,434,668	Accuracy	Temporal Per User
2016	[148]	GE	184	Gowalla	107,092	1,280,969	6,442,892	Accuracy	Temporal Per User
2017	[153]	PACE	153	Gowalla	18,737	32,510	1,278,274	P, R, NDCG, MAP	Temporal Per User
2017	[153]	PACE	153	Yelp	30,887	18,995	860,888	P, R, NDCG, MAP	Temporal Per User
2018	[143]	GeoIE	49	Foursquare	6,118	88,193	172,961	P, R	Temporal Per User
2018	[143]	GeoIE	49	Gowalla	1,624	3,585	115,890	P, R	Temporal Per User
2019	[182]	STGN	45	Foursquare (CA)	49,005	206,097	425,691	Accuracy, MAP	Temporal Per User
2019	[182]	STGN	45	Foursquare (SIN)	30,887	18,995	860,888	Accuracy, MAP	Temporal Per User
2019	[182]	STGN	45	Gowalla	18,737	32,510	1,278,274	Accuracy, MAP	Temporal Per User
2019	[182]	STGN	45	Brightkite	51,406	772,967	4,747,288	Accuracy, MAP	Temporal Per User
2020	[147]	TECF	14	Foursquare	2,321	5,596	194,108	P, R	Random Per User
2020	[147]	TECF	14	Foursquare	10,162	24,250	456,988	P, R	Random Per User

Data examining and understanding

- Figure a and b Investigate the relation between the similarity of pairwise users and their physical distance
- Figure c and d Examine the correlation between friends



Joint Geographical Modeling and Matrix Factorization for POI Recommendation



latent interest

user latent vectors

user activity area vectors

$$\min_{\mathbf{P},\mathbf{Q},\mathbf{X}} \|\mathbf{W}\odot(\mathbf{R}-\boxed{\mathbf{P}\mathbf{Q}^T}-\boxed{\mathbf{X}\mathbf{Y}^T})\|_F^2+\gamma(\|\mathbf{P}\|_F^2+\|\mathbf{Q}\|_F^2)+\lambda\|\mathbf{X}\|_1$$

geography

$$\text{subject to } \mathbf{X} \geq 0$$

POI latent vectors

Defu Lian, Cong Zhao, Xing Xie, Guangzhong Sun, Enhong Chen, Yong Rui: GeoMF: joint geographical modeling and matrix factorization for point-of-interest recommendation. KDD 2014.

Geographical Modeling

- Recall that the locality of users' activity and POIs' influences

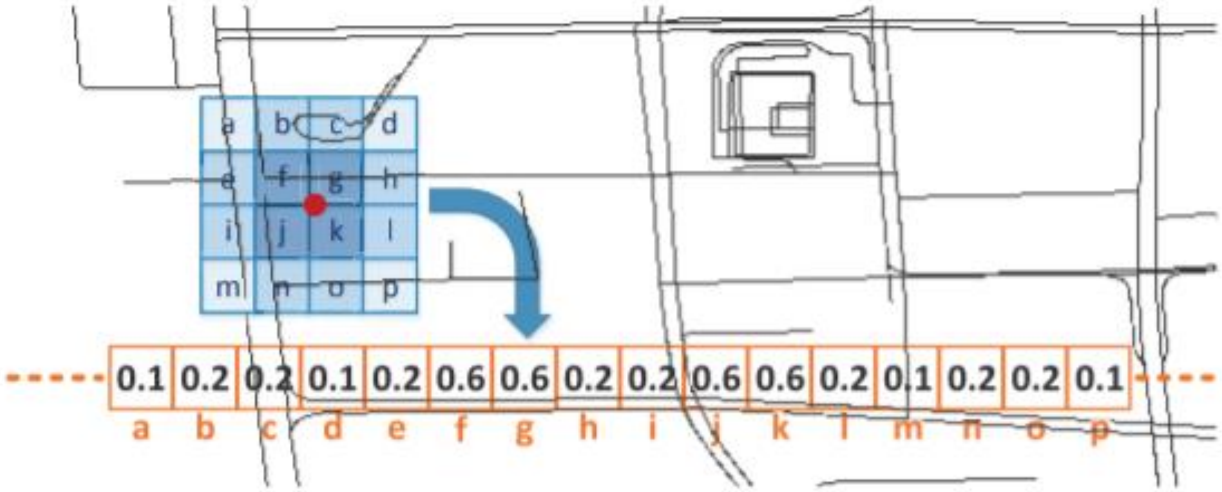
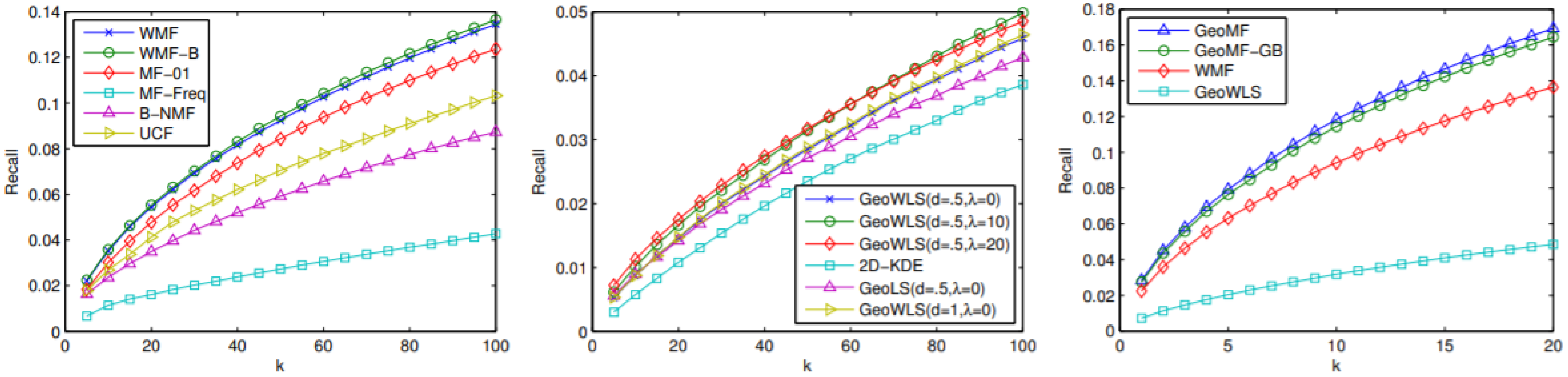


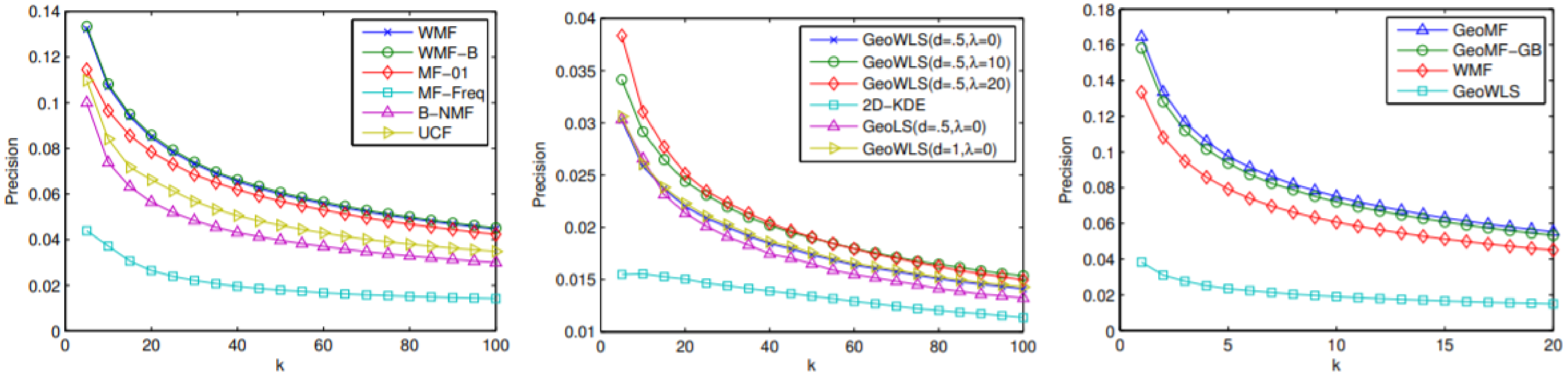
Figure 2: Generating an influence area vector for a POI (the red point).

Defu Lian, Cong Zhao, Xing Xie, Guangzhong Sun, Enhong Chen, Yong Rui: GeoMF: joint geographical modeling and matrix factorization for point-of-interest recommendation. KDD 2014.

Experimental Results



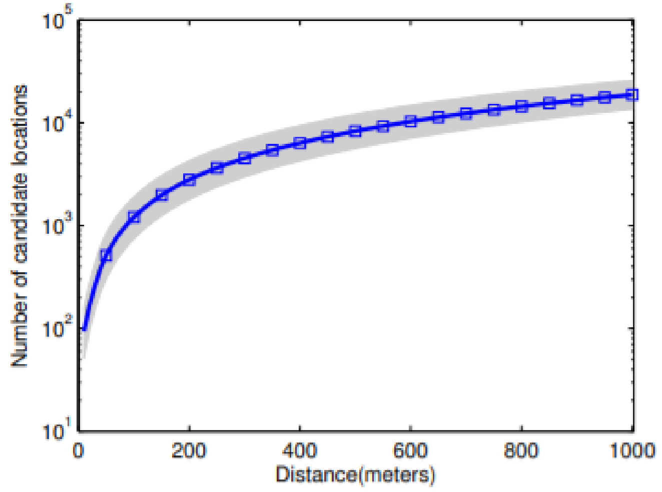
(a) Recall-MF-Comparision (b) Recall-GeoWLS-Comparision (c) Recall-GeoMF-Comparision



(d) Precision-MF-Comparision (e) Precision-GeoWLS-Comparision (f) Precision-GeoMF-Comparision

Experimental Results

- Figure a studies the relation between expansion distance and the number of candidates.
- Figure b shows the density plot of activity areas of one user



(a)

(b)

Multi-spatial domain recommender systems

- Preliminary of multi-spatial domain recommender systems
- Multi-geographic point modeling for location-based recommendation
- Multi-system/sites modeling for multidomain recommendation

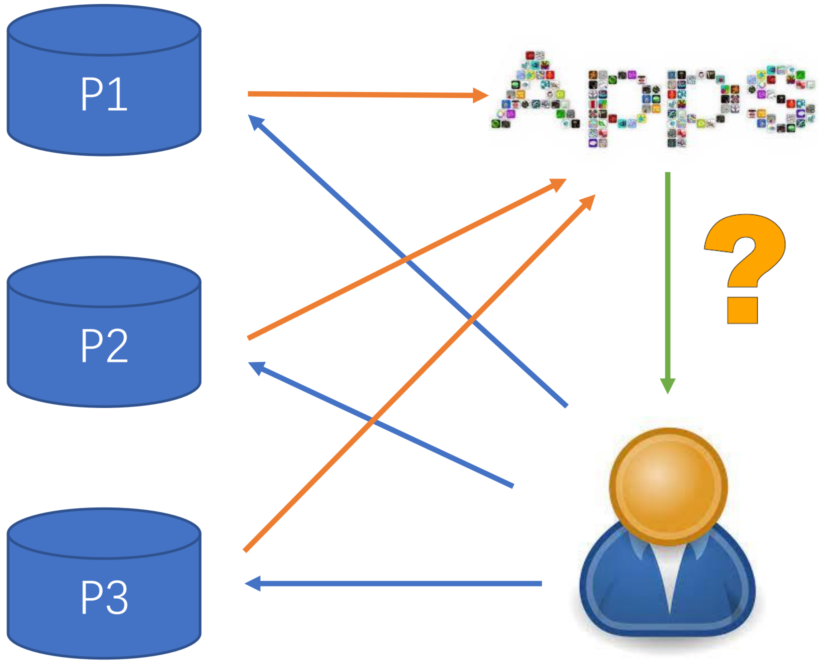
Multi-system/sites recommendation

Multi-system/sites recommendation aims to integrate different parties (e.g., systems or sites) of user data to provide recommendation service.

User records are stored in multi-system/sites

Data sharing and transporting issues:

- data security
- data privacy
- data access rights

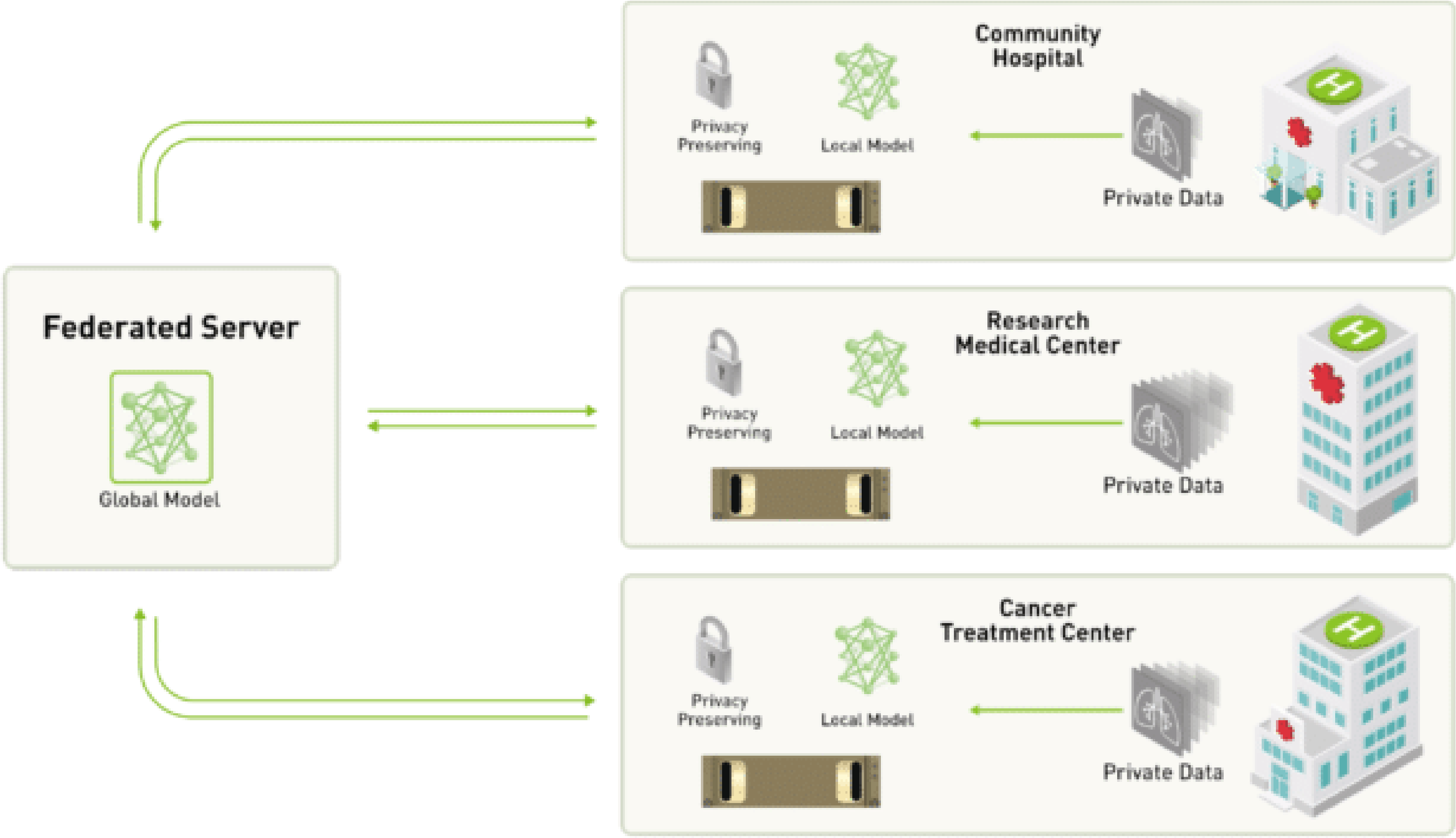


Federated learning

A machine learning technique that trains an algorithm across multiple decentralized edge devices or servers holding local data samples, without exchanging them – Wikipedia.

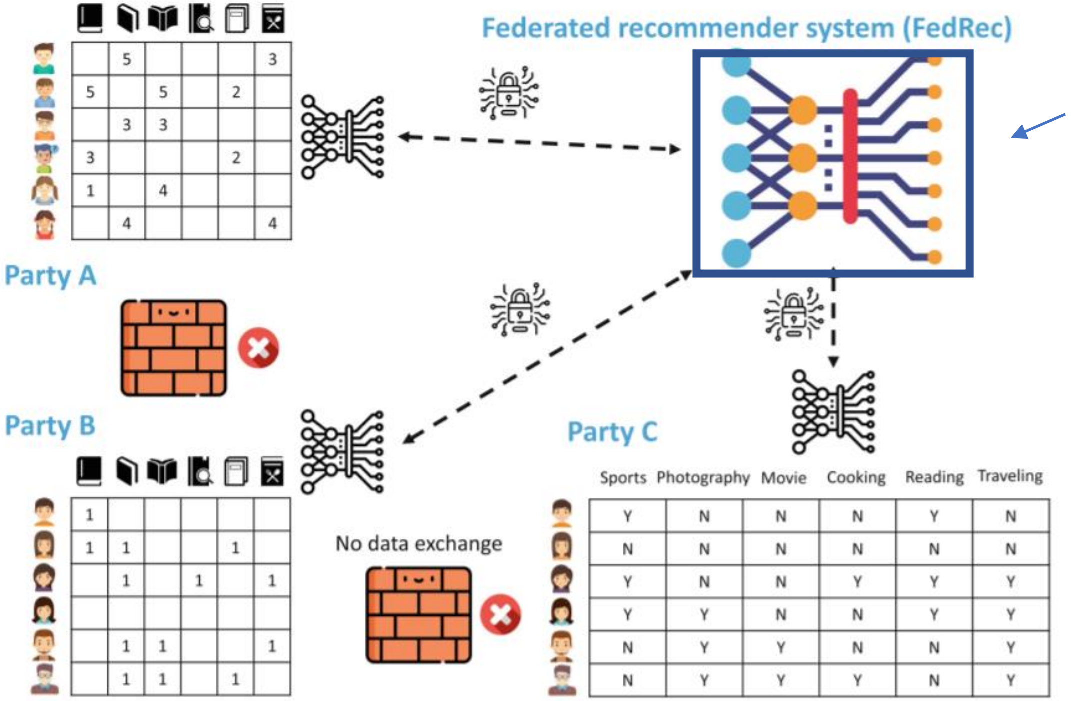
.General principle:

- training local models on local data samples
- exchanging parameters between these local nodes
- generating a global model shared by all nodes.



Federated Recommendation (FedRec)

- FedRec aims to collaboratively train recommendation model(s) among multiple parties without direct access to the private data of each other



recommender systems

Fig. 1. The illustration of a Federated Recommender System. FedRec addresses the data silo issue and builds recommender systems without compromising privacy and security.

Liu Yang, Ben Tan, Vincent W. Zheng, Kai Chen, Qiang Yang: Federated Recommendation Systems. Federated Learning 2020: 225-239

General objectives

- Compared to the conventional RSs, FedRec primarily protects user privacy and data security through decentralizing private user data locally at each party.

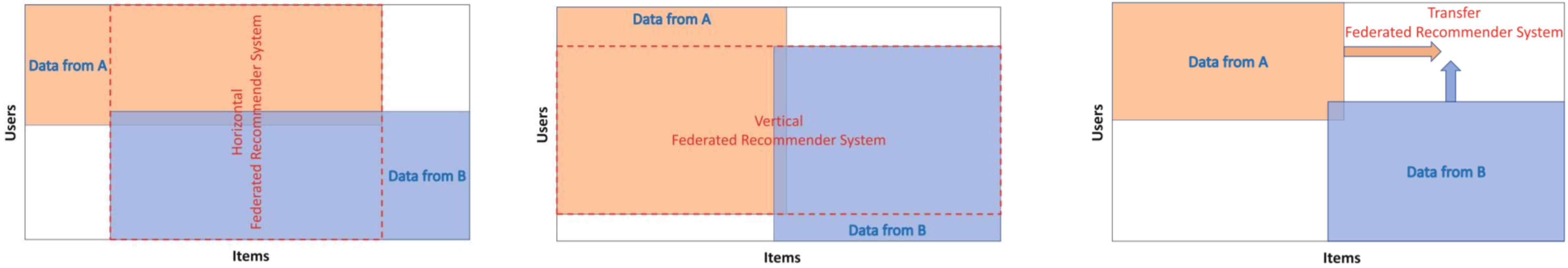
$$\arg\min_{\tilde{\boldsymbol{\theta}}_k} \sum_{k=1}^{K} L(\boldsymbol{R}_k, f_{\tilde{\boldsymbol{\theta}}_k}^{fed}(\mathcal{U}_k, \mathcal{I}_k | \mathcal{G}_k, z(\mathcal{G}_{k' \in \{1,\ldots,K\} \setminus \{k\}}), z(\mathcal{D}_{h \in \{1,\ldots,H\}}))),$$

$$|V(f_{\tilde{\boldsymbol{\theta}}_k}^{fed}) - V(f_{\boldsymbol{\theta}_k})| > \delta \quad and \quad |V(f_{\tilde{\boldsymbol{\theta}}_k}^{sum}) - V(f_{\tilde{\boldsymbol{\theta}}_k}^{fed})| \leq \epsilon,$$

Liu Yang, Ben Tan, Vincent W. Zheng, Kai Chen, Qiang Yang: Federated Recommendation Systems. Federated Learning 2020: 225-239

Categorization of FedRec

- According to the data structure of the RS, FedRec can be divided into Horizontal FedRec, Vertical FedRec and Transfer FedRec



(a) Horizontal FedRec. Items are shared, but users are different between parties.

(b) Vertical FedRec. Users are shared, but items are different between parties.

(c) Transfer FedRec. Neither users nor items are shared between parties.

Liu Yang, Ben Tan, Vincent W. Zheng, Kai Chen, Qiang Yang: Federated Recommendation Systems. Federated Learning 2020: 225-239

Horizontal FedRec

- Several works including Federated Collaborative Filter (FCF), focus on this scenario.

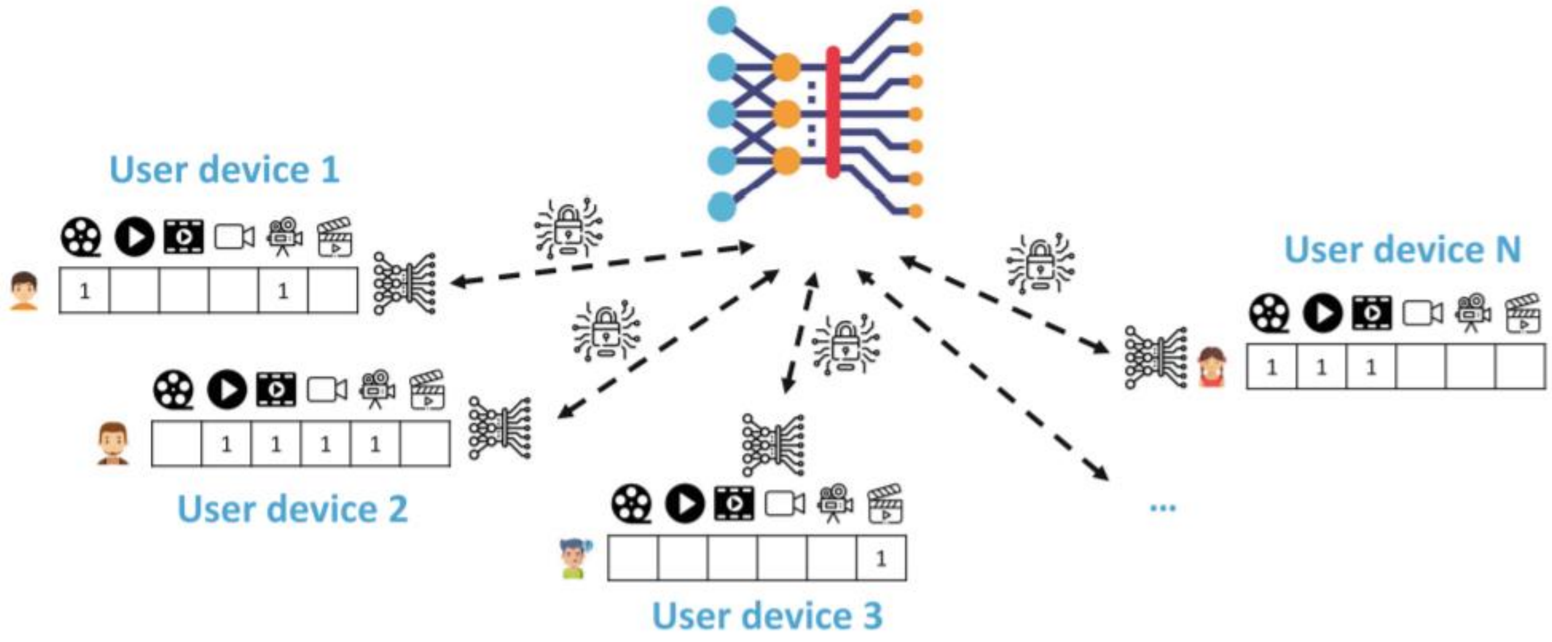


Fig. 3. The typical scenario of Horizontal FedRec. Each party is the device of an individual user. They share the same items but have different users.

Vertical FedRec

- Several existing works have been designed for such a feature distributed learning problem where party A and B hold different item sets.

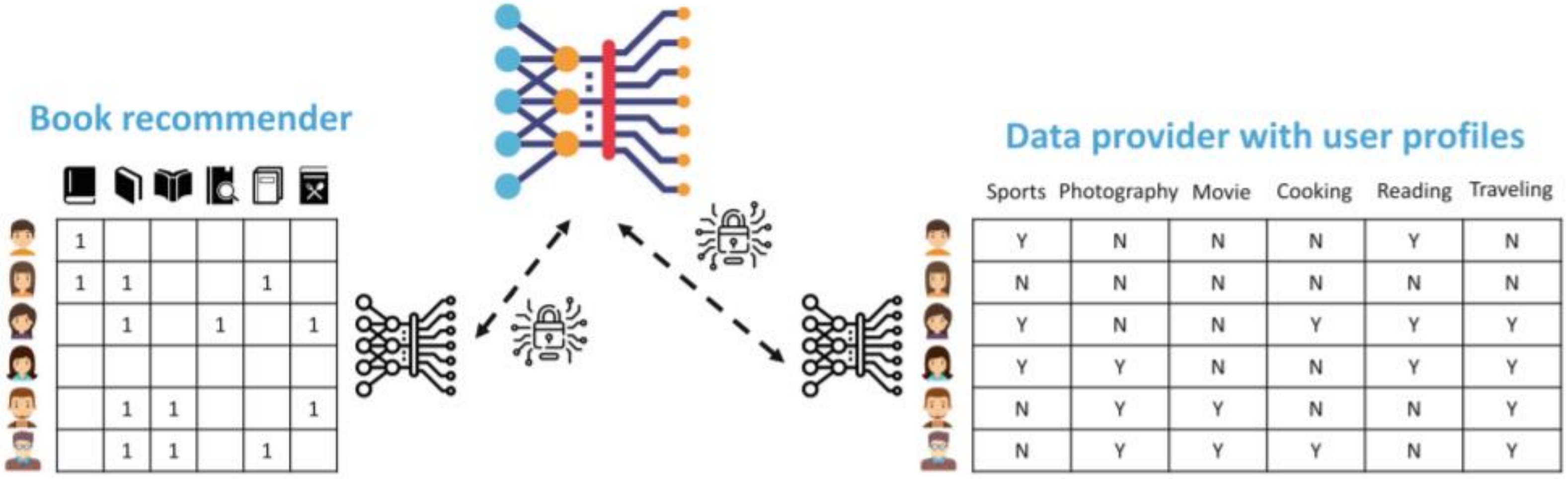


Fig. 4. The typical scenario of Vertical FedRec. One party is a book recommender, while the other one is a data provider with user profiles. They share the same users but have different items.

Hu, Y., Niu, D., Yang, J., Zhou, S.: FDML: a collaborative machine learning framework for distributed features, KDD'18
Kewei Cheng, Tao Fan, et al.: SecureBoost: A Lossless Federated Learning Framework. CoRR abs/1901.08755 (2019)

Transfer FedRec

- A popular book recommender system in region A wants to help another new movie recommender system in region B to collaboratively learn a movie recommendation model.

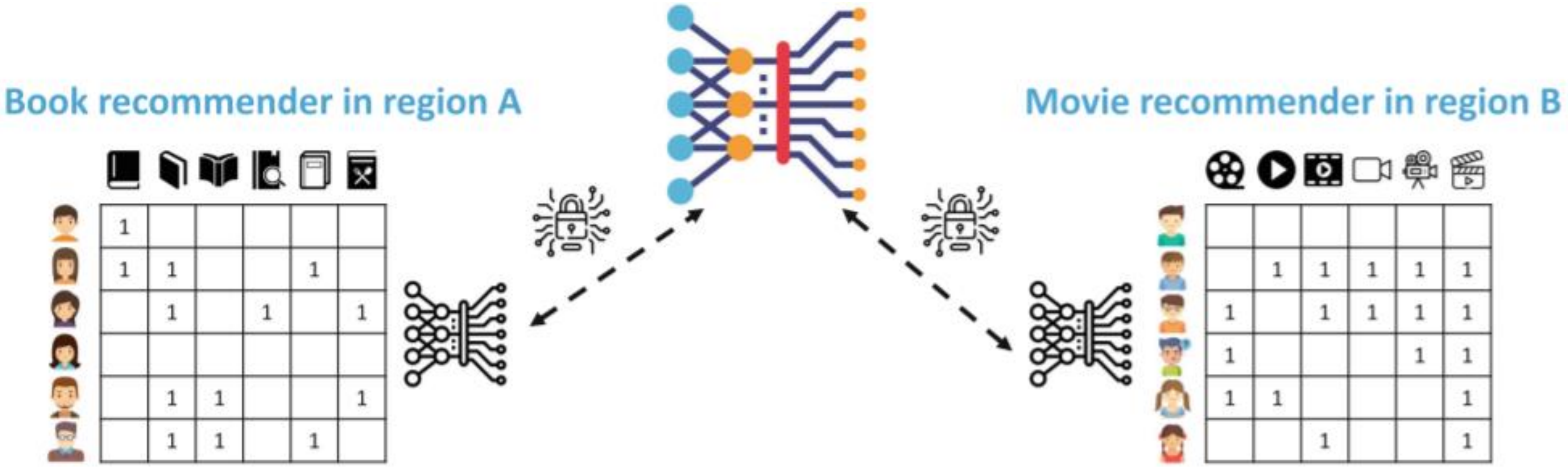


Fig. 5. The typical scenario of Transfer FedRec. One party is a book recommender, while the other one is a movie recommender in the different region. They share neither users nor items.

Sharma, S., Chaoping, X., Liu, Y., Kang, Y.: Secure and efficient federated transfer learning. arXiv 2019.

Open issues

Important issues to be solved:

- Communication Cost in FedRec
- Flexibility and Scalability in FedRec
- Non-IID Data in FedRec.

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