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Local Collaborative Autoencoders

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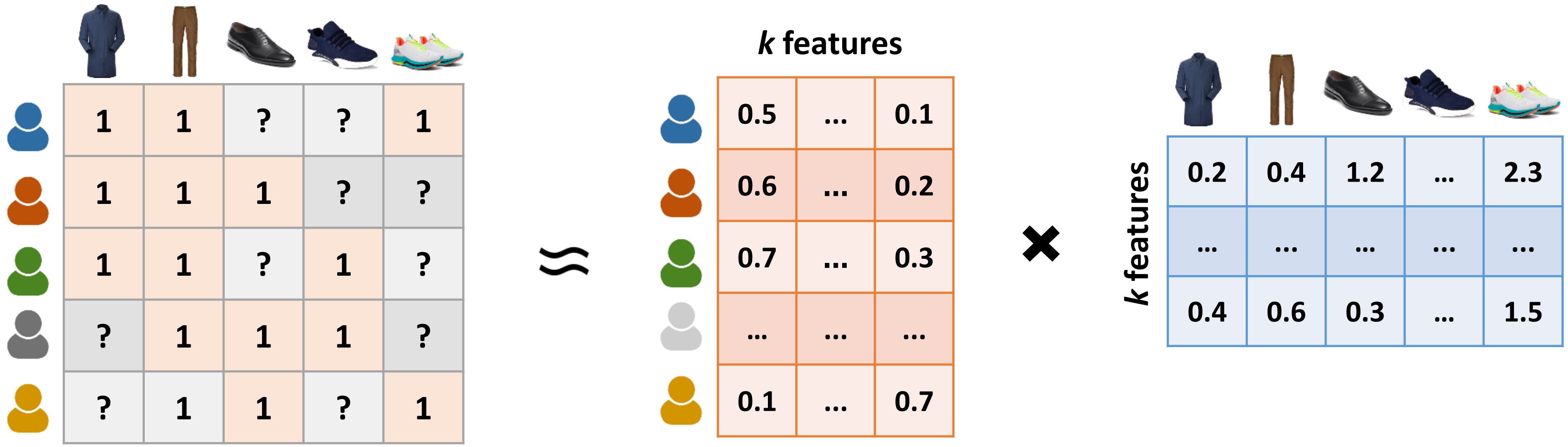
Motivation

Global Low-rank Assumption

➢ **Existing models are based on the global low-lank assumption.**

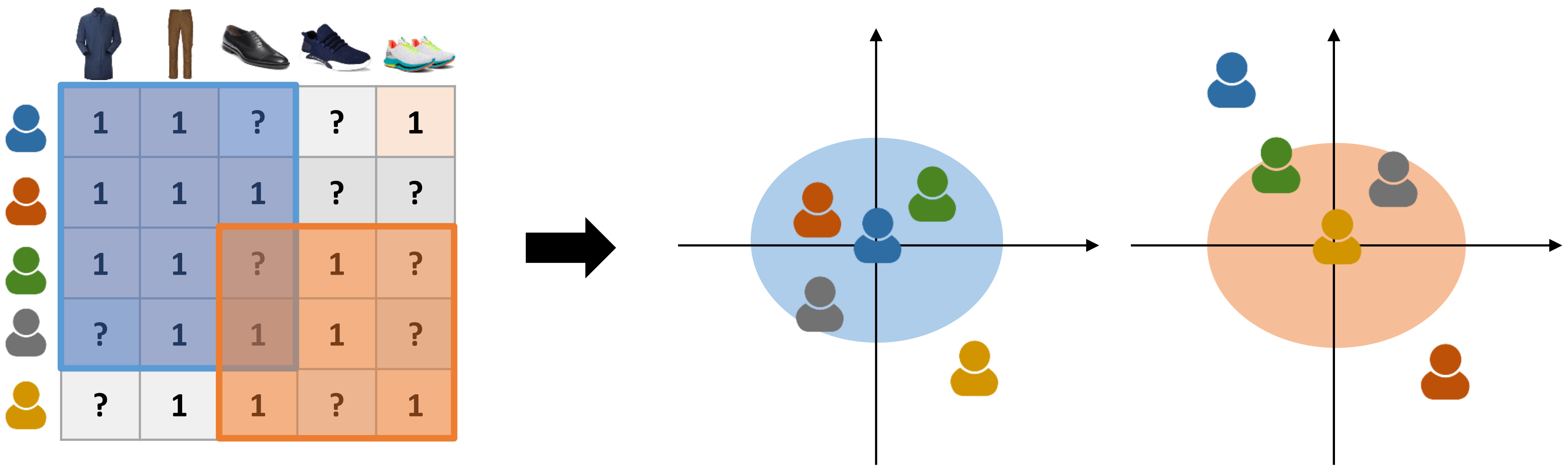
- All users and items share the **same** latent features.



➢ **Limitation: some users/items may have different latent features.**

Local Low-rank Assumption

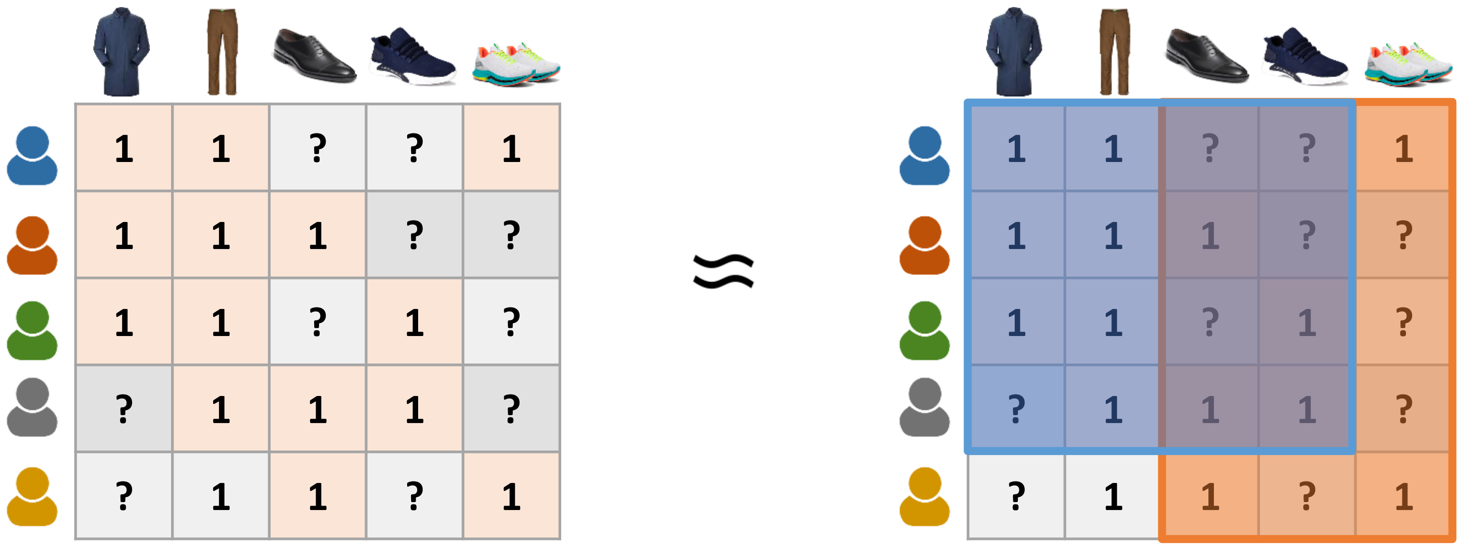
- **A user-item matrix can be divided to several sub-matrices with the local low-rank assumption.**
  - Each sub-matrix represents **different** communities.
  - Local models represent various communities with **different** characteristics.



Limitation of Existing Local Models

➢**If the local model is too large, it is close to the global model.**

- Because LLORMA uses **large local models**, the local model may not represent its unique characteristic.
- The performance gain may come from an **ensemble effect**.

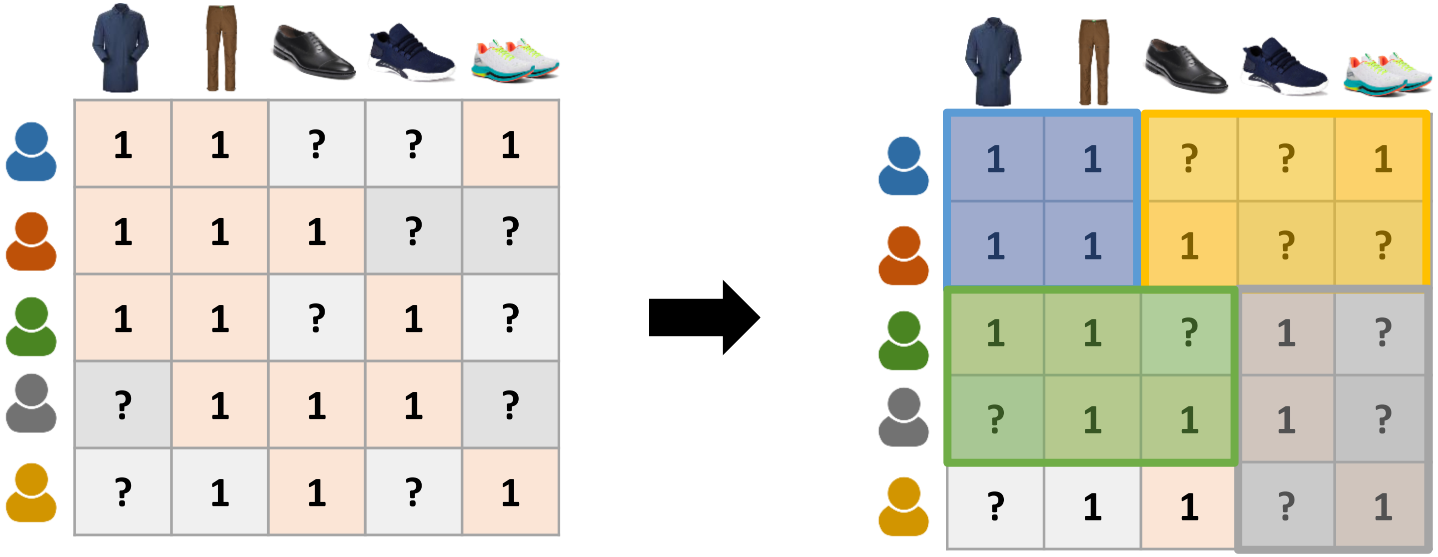


Lee et al., "LLORMA: Local Low-Rank Matrix Approximation," JMLR 2016

Limitation of Existing Local Models

➢ **If the local model is too small, the accuracy is too low.**

- Because sGLSVD uses **small local models**, some local model may have insufficient training data.



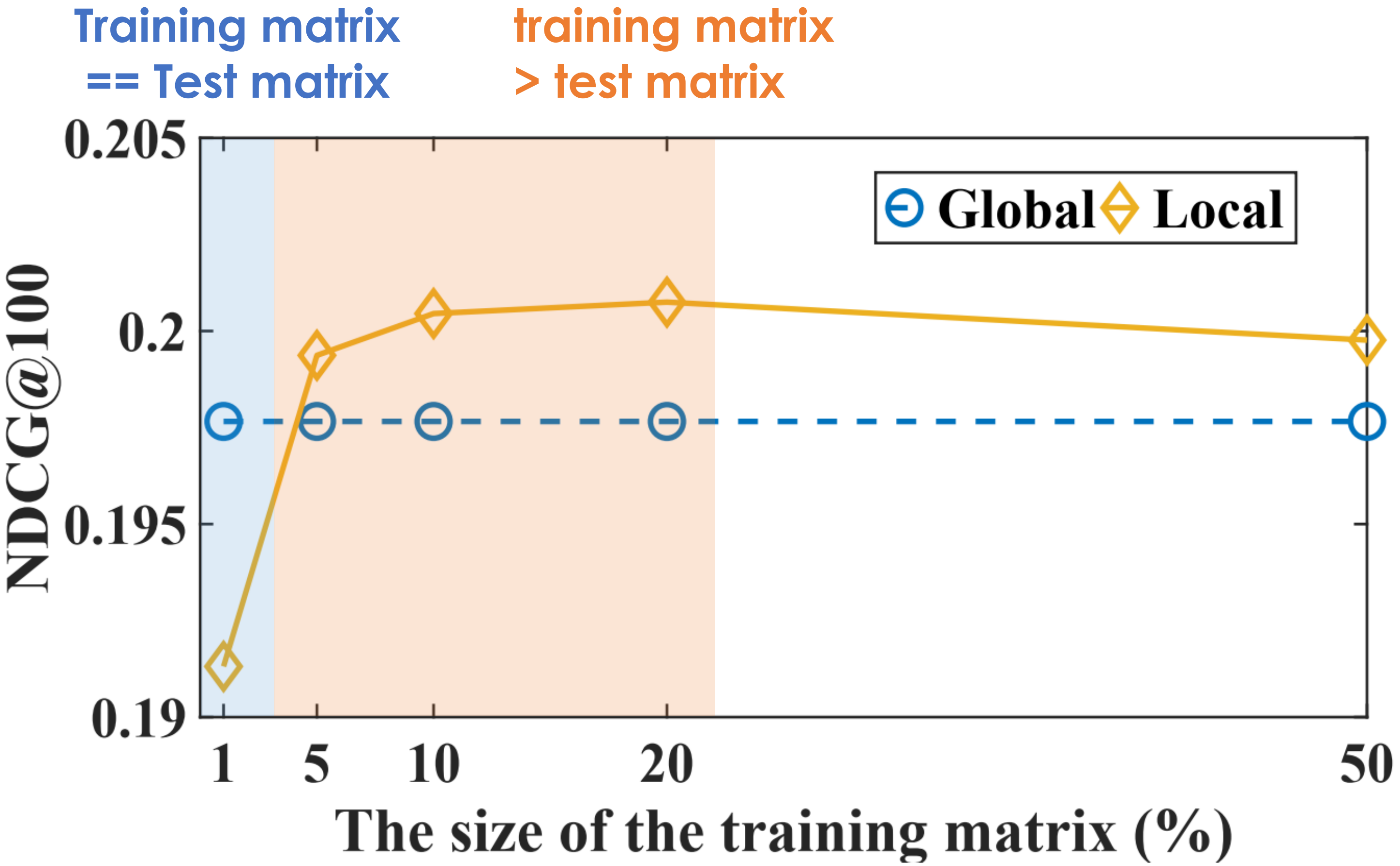
Evangelia Christakopoulou and George Karypis, "Local Latent Space Models for Top-N Recommendation," KDD 2018

Research Question

How to build coherent and accurate local models?

Our Key Contributions

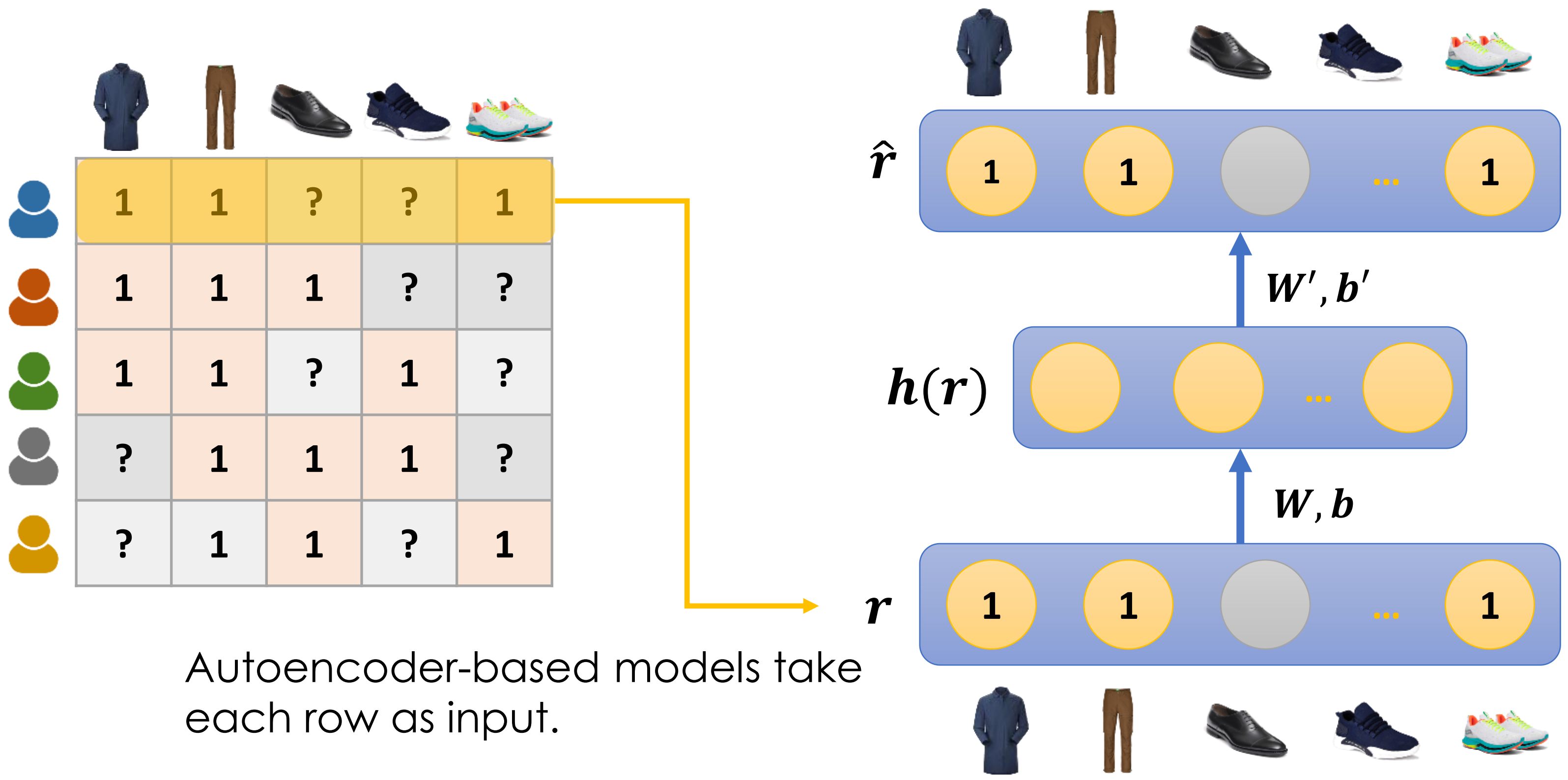
- When the local model keeps small and coherent, we build the local model with a relatively **large training data**.



(Dataset: ML10M)

Our Key Contributions

- **Autoencoder-based models are used as the base model to train the local model.**
  - They are useful for capturing **non-linear and complicated patterns.**



Autoencoder-based models take each row as input.

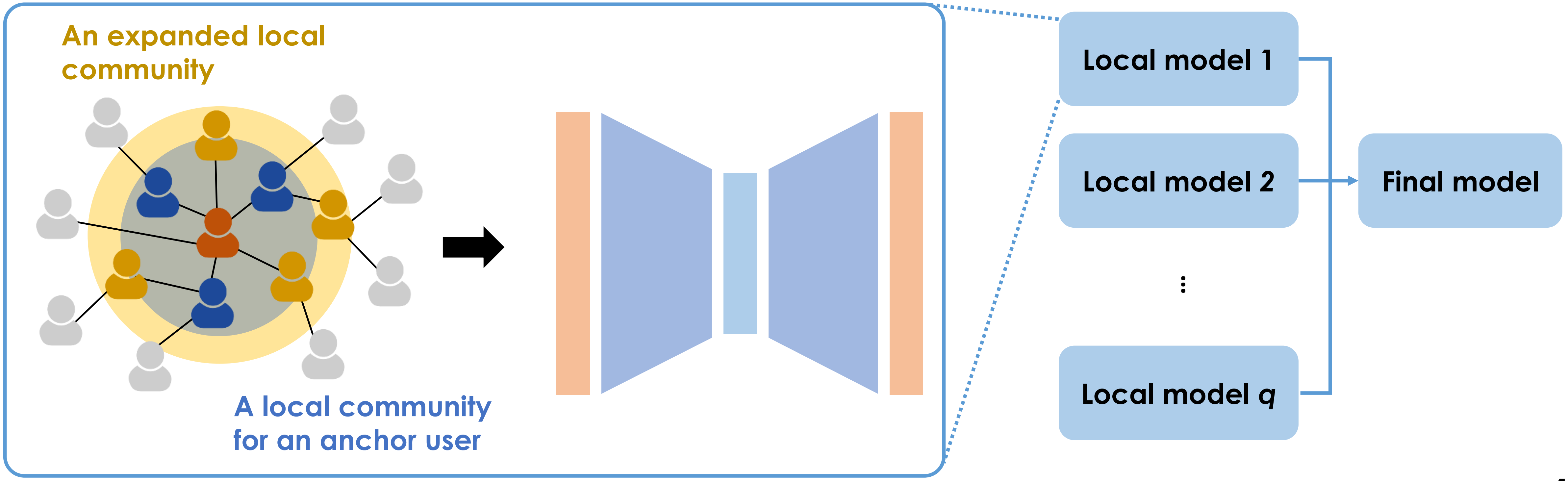
Sedhain et al., "AutoRec: Autoencoders Meet Collaborative Filtering," WWW 2015

Proposed Method

Local Collaborative Autoencoders (LOCA)

➢Overall architecture of LOCA

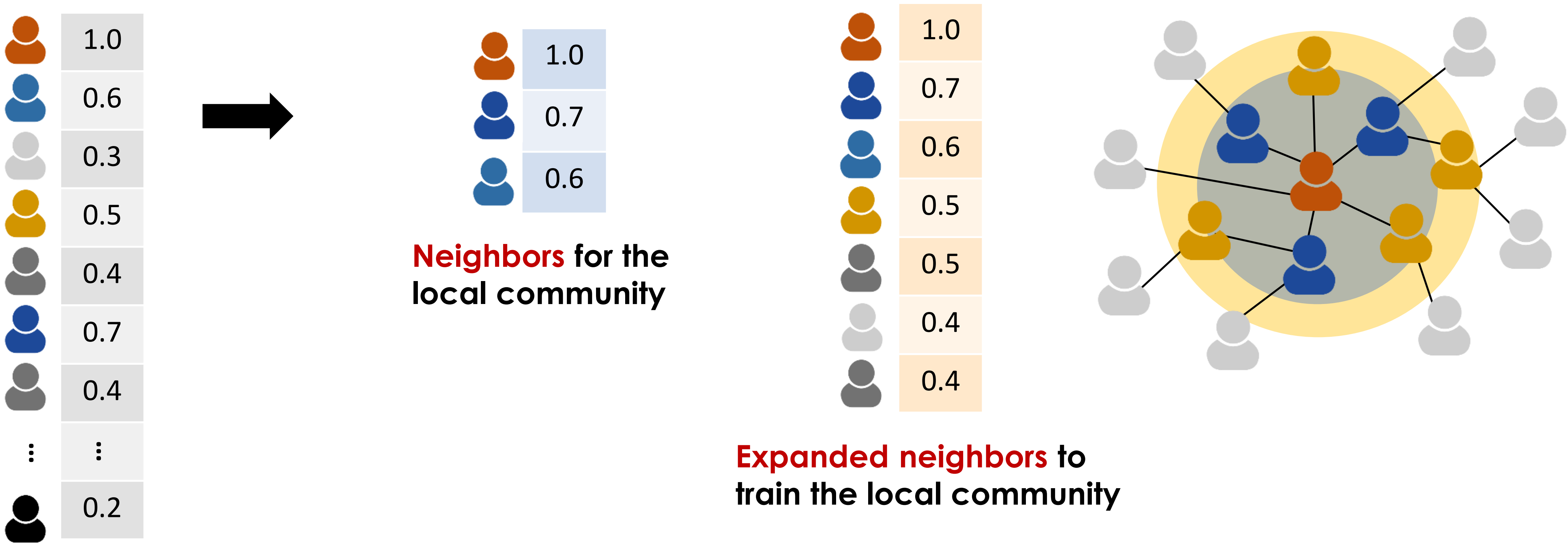
- Step 1: Discovering two **local communities** for an anchor user
- Step 2: Training a local model with **an expanded community**
- Step 3: **Combining** multiple local models



Step 1: Discovering Local Communities

➢ For an anchor user, **determine** a local community and **expand** the local community for training.

Calculate the similarities between the anchor user and the other users.



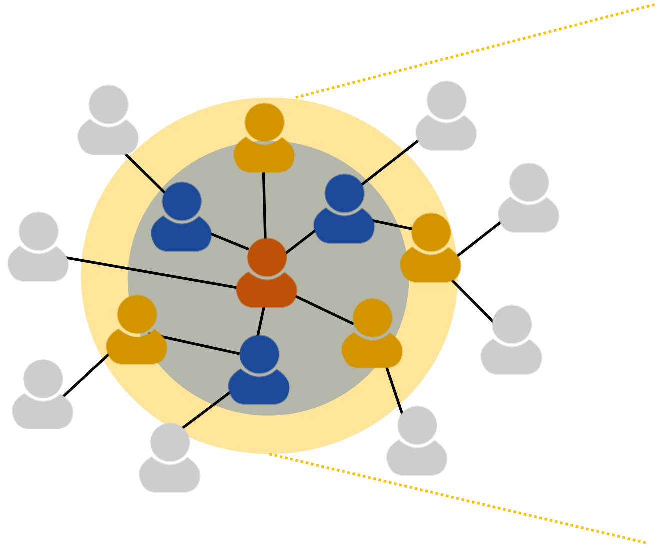
Neighbors for the local community

Expanded neighbors to train the local community

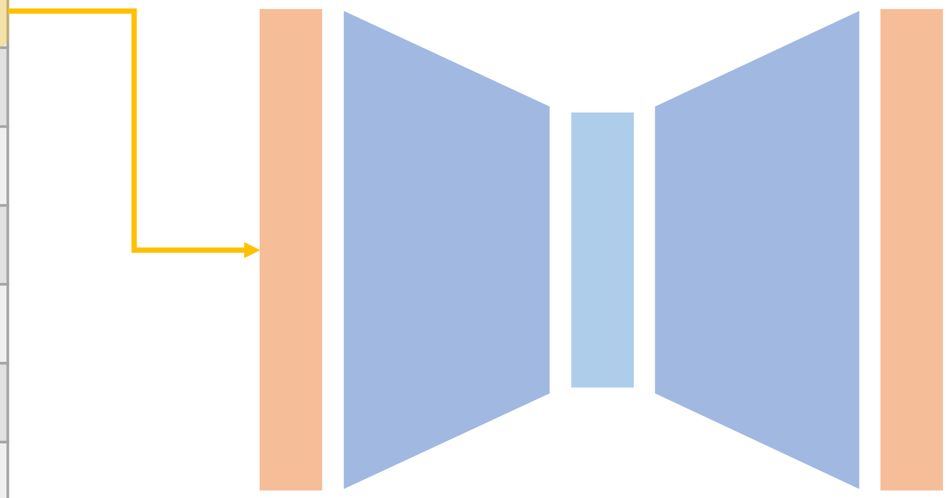
Step 2: Training a Local Model

➢ **Train the local model with the expanded community.**

- Use the **autoencoder-based model** for training the local model.
  - Note: It is possible to utilize any base models, e.g., MF, AE and EASE^R.
- The similarities with the anchor are used for the **user weights** for training.



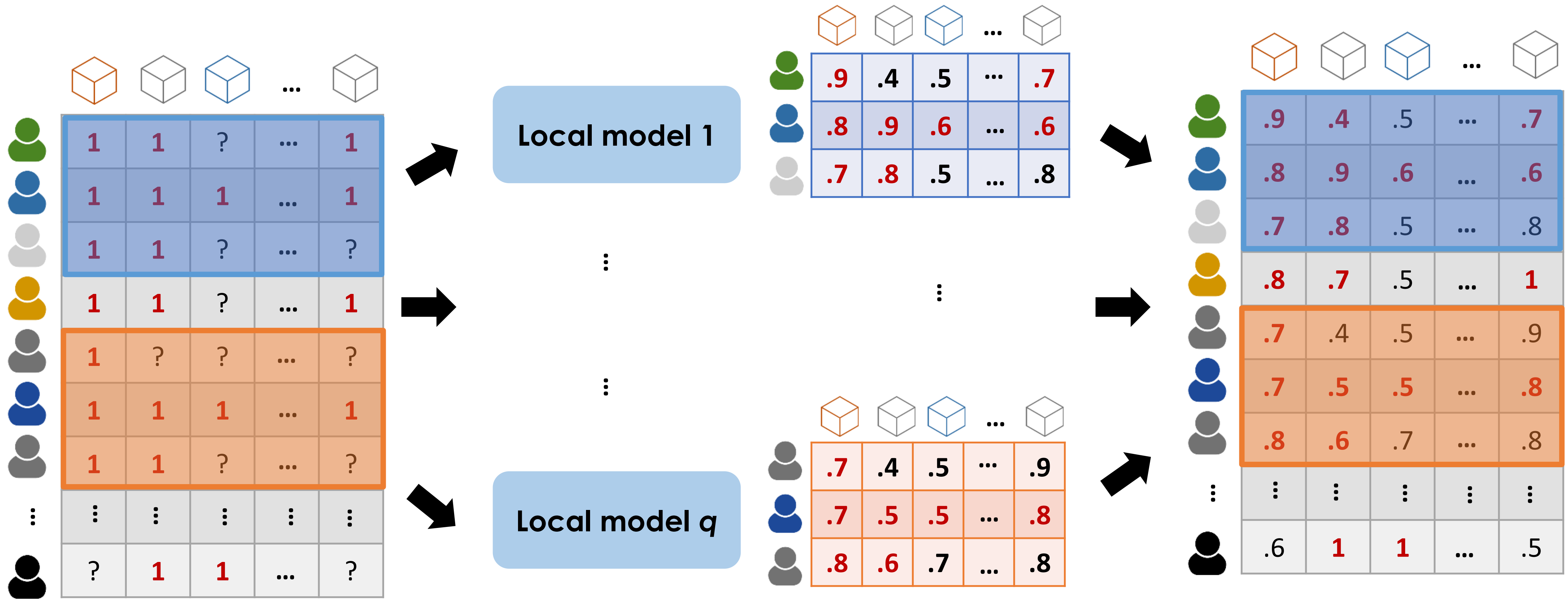
				…	
1.0	1	1	?	…	1
0.6	1	1	1	…	1
0.3	1	1	?	…	?
0.5	1	1	?	…	1
0.4	1	?	?	…	?
0.7	1	1	1	…	1
0.4	1	1	?	…	?



Harald Steck., "Embarrassingly shallow autoencoders for sparse data," WWW 2019.

Step 3: Combining Multiple Local Models

- **Aggregate** multiple local models with the weight of each local model.



Training Local Models in Detail

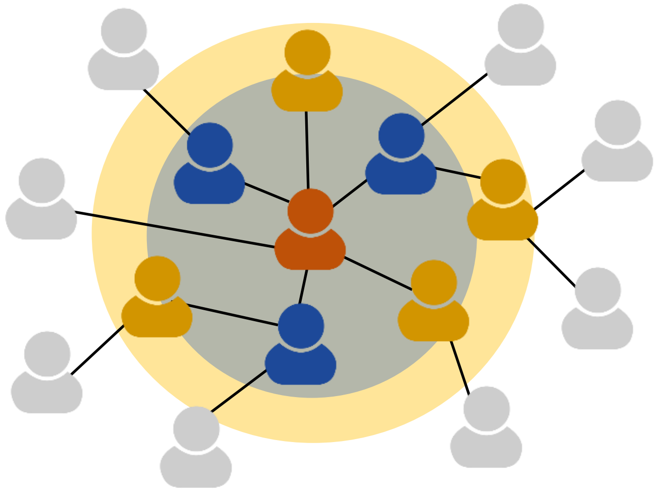
➢The loss function for the j-th local model

User weight for training the j-th local model

$$\underset{\theta^{(j)}}{\operatorname{argmin}} \sum_{r_u \in R} t_u^{(j)} \mathcal{L}\left(\boldsymbol{r}_u, \boldsymbol{M}^{local}(\boldsymbol{r}_u; \boldsymbol{\theta}^{(j)})\right) + \boldsymbol{\lambda}\boldsymbol{\Omega}(\boldsymbol{\theta}^{(j)})$$

The j-th local model

Parameter for the j-th local model



➢Aggregating all local models and a global model

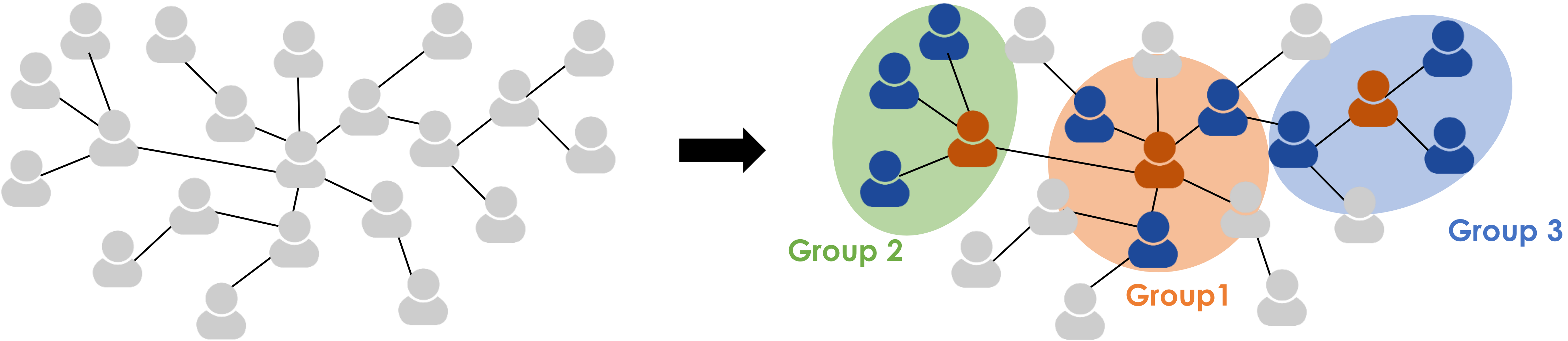
The global model is used to handle the users who are not covered by local models.

User weight for inferring the j-th local model

$$\widehat{\boldsymbol{R}} = \boldsymbol{\alpha} \boldsymbol{M}^{global}\left(\boldsymbol{R}; \boldsymbol{\theta}^{(g)}\right) + (\mathbf{1} - \boldsymbol{\alpha}) \sum_{j=1}^{q} \boldsymbol{w}^{(j)} \odot \boldsymbol{M}^{local}\left(\boldsymbol{R}; \boldsymbol{\theta}^{(j)}\right) \oslash \boldsymbol{w}$$

How to Choose Anchor Users

- **Random selection: Choose k anchor users at random.**
- **Need to maximize the coverage of users by local models.**
  - An optimal maximum coverage algorithm is the NP-hard problem.
- **Use the greedy method to maximize the coverage.**
  - Select the anchor user who has the most uncovered users iteratively.



Experiments

Experimental Setup: Dataset

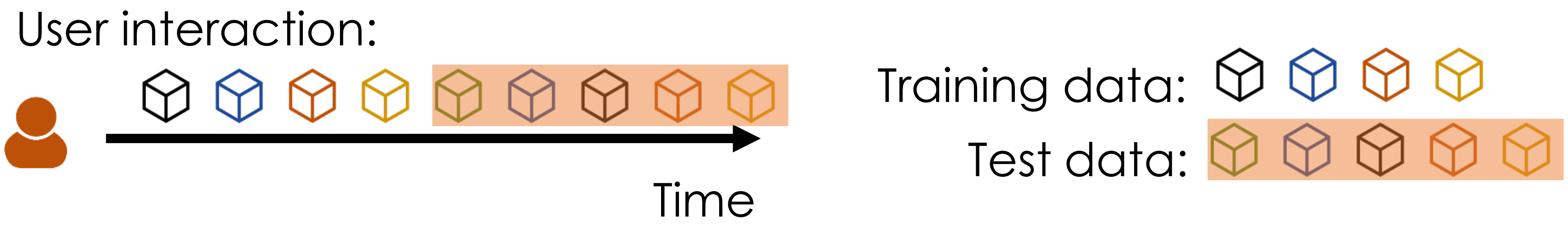
- **We evaluate our model over five public datasets with various characteristics (e.g., domain, sparsity).**

Dataset	# of users	# of items	# of ratings	Sparsity
MovieLens 10M (ML10M)	69,878	10,677	10,000,054	98.66%
MovieLens 20M (ML20M)	138,493	26,744	20,000,263	99.46%
Amazon Music (AMusic)	4,964	11,797	97,439	99.83%
Amazon Game (AGame)	13,063	17,408	236,415	99.90%
Yelp	25,677	25,815	731,671	99.89%

Evaluation Protocol and Metrics

➢Evaluation protocol: leave-5-out

- Hold-out the last 5 interactions as the test data for each user.



➢Evaluation metrics

- Recall@100
  - Measures the number of test items included in the top-N list.
- NDCG@100
  - Measures the ranking of test items in the top-N list.

Competitive Global/Local Models

- **Four autoencoder-based global models**
  - **CDAE**: a denoising autoencoder-based model with a latent user vector
  - **MultVAE**: a VAE-based model
  - **RecVAE**: a VAE-based model by improving MultVAE
  - **EASE^R**: an item-to-item latent factor model

- **Two local models**
  - **LLORMA**: local model using MF as the base model
  - **sGLSVD**: local model using SVD as the base model

Yao Wu et al., "Collaborative Denoising Auto-Encoders for Top-N Recommender Systems," WSDM 2016
Dawen Liang et al., "Variational autoencoders for collaborative filtering," WWW 2018.
Ilya Shenbin et al., "RecVAE: A new variational autoencoder for Top-N recommendations with implicit feedback," WSDM 2020.
Harald Steck., "Embarrassingly shallow autoencoders for sparse data," WWW 2019.
Lee et al., "LLORMA: Local Low-Rank Matrix Approximation," JMLR 2016
Evangelia Christakopoulou and George Karypis, "Local Latent Space Models for Top-N Recommendation," KDD 2018

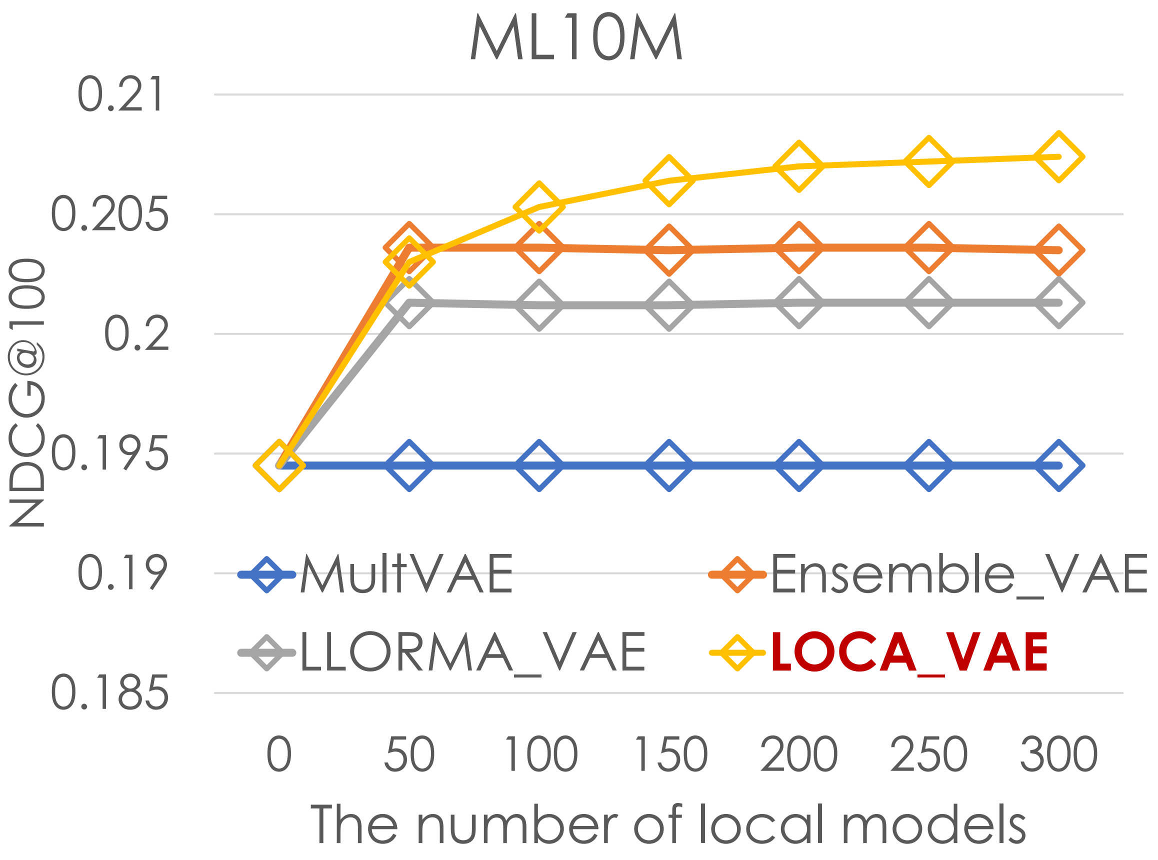
Accuracy: LOCA vs. Competing Models

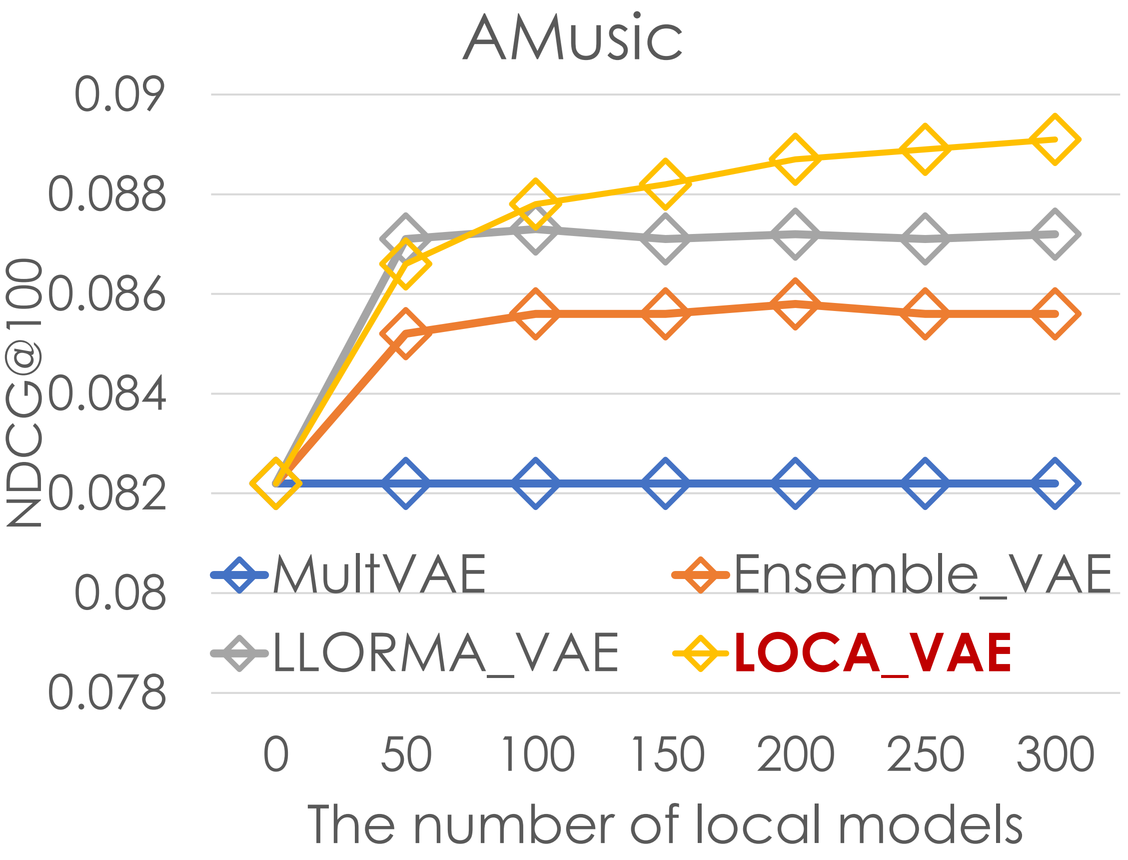
- **LOCA consistently outperforms** competitive global/local models over five benchmark datasets.

		Global Models				Local Models		Ours	
Dataset	**Metric**	**CDAE**	**MultVAE**	**$EASE^R$**	**RecVAE**	**LLORMA**	**sGLSVD**	**$LOCA_{VAE}$**	**$LOCA_{EASE}$**
ML10M	**Recall@100**	0.4685	0.4653	0.4648	*0.4705*	0.4692	0.4468	**0.4865**	0.4798
	NDCG@100	0.1982	0.1945	0.2000	0.1996	*0.2042*	0.1953	**0.2073**	0.2049
ML20M	**Recall@100**	0.4324	0.4397	*0.4468*	0.4417	0.3355	0.4342	0.4419	**0.4654**
	NDCG@100	0.1844	0.1860	*0.1948*	0.1857	0.1446	0.1919	0.1884	**0.2024**
Amusic	**Recall@100**	0.0588	0.0681	*0.0717*	0.0582	0.0517	0.0515	**0.0748**	0.0717
	NDCG@100	0.712	*0.0822*	0.0821	0.0810	0.0638	0.0613	**0.0893**	0.0826
Agames	**Recall@100**	0.1825	*0.2081*	0.1913	0.1920	0.1223	0.1669	**0.2147**	0.1947
	NDCG@100	0.0808	*0.0920*	0.0915	0.0849	0.0539	0.0777	**0.0966**	0.0922
Yelp	**Recall@100**	0.2094	*0.2276*	0.2187	0.2262	0.1013	0.1965	**0.2354**	0.2205
	NDCG@100	0.0920	*0.0982*	0.0972	0.0975	0.0429	0.0857	**0.1103**	0.0981

Effect of the Number of Local Models

- **The accuracy of LOCA improved consistently with an increase in the number of local models.**





Effect of Anchor Selection Method

➢ **Our coverage-based anchor selection outperforms the other methods in terms of accuracies and coverages.**

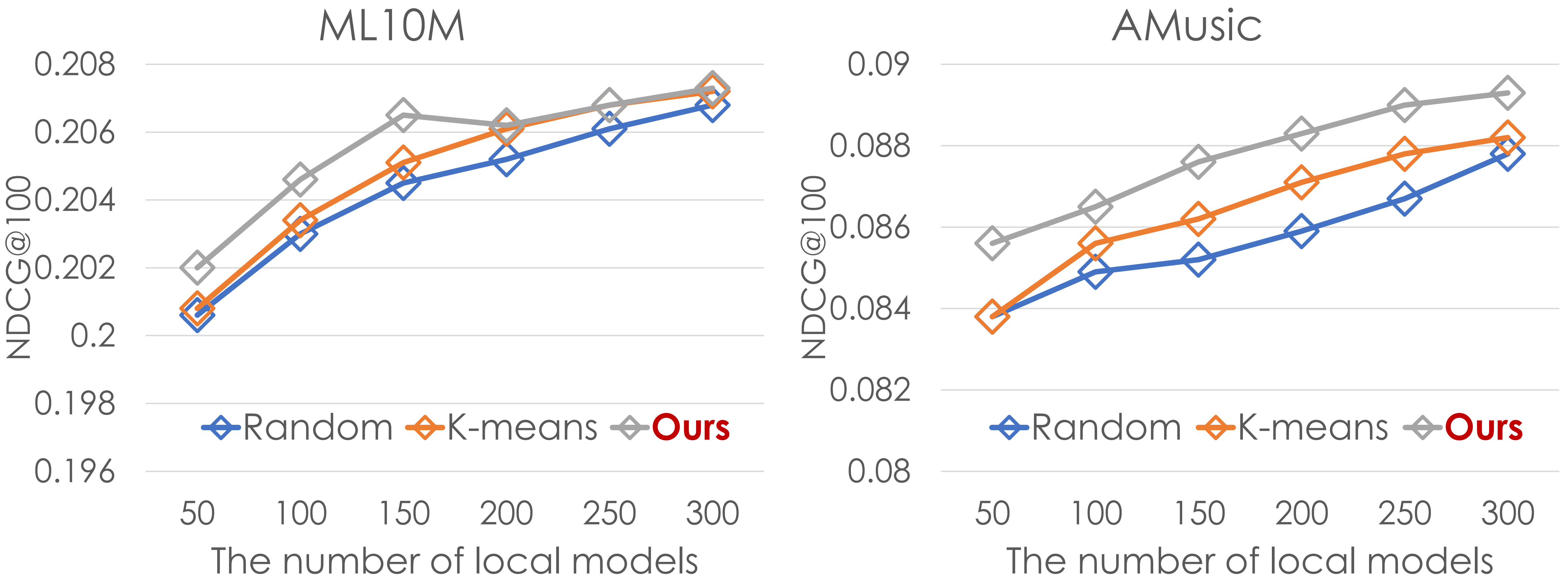
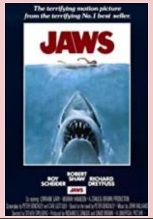
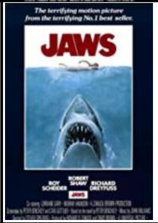


Illustration of LOCA

➢ **When a user has multiple tastes, LOCA can capture the user preference by combining different local patterns.**

- For a user (66005 in ML10M) who likes Sci-Fi and Horror movies, LOCA shows a better accuracy.

Recommendation	Local 70	Local 179	Global	Ground Truth
Top-1	 Sci-Fi Adventure	 Horror Action	 Thriller Action	 Sci-Fi Action
Top-2	 Sci-Fi Horror	 Horror Drama	 Drama	 Horror Thriller
Top-3	 Sci-Fi Action	 Horror Drama	 Drama Mystery	 Horror Action

Conclusion

Conclusion

- **We propose a new local recommender framework, namely local collaborative autoencoders (LOCA).**

- **LOCA can handle a large number of local models effectively.**
  - Adopts a local model with different training/inference strategies.
  - Utilizes autoencoder-based model as the base model.
  - Makes use of a greedy maximum coverage method to build various local models.

- **LOCA outperforms the state-of-the-art global and local models over various benchmark datasets.**

Q&A

Email: zxcvxd@skku.edu

Code: https://github.com/jin530/LOCA