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HGAR: Hybrid Granular Algorithm for Rating Recommendation

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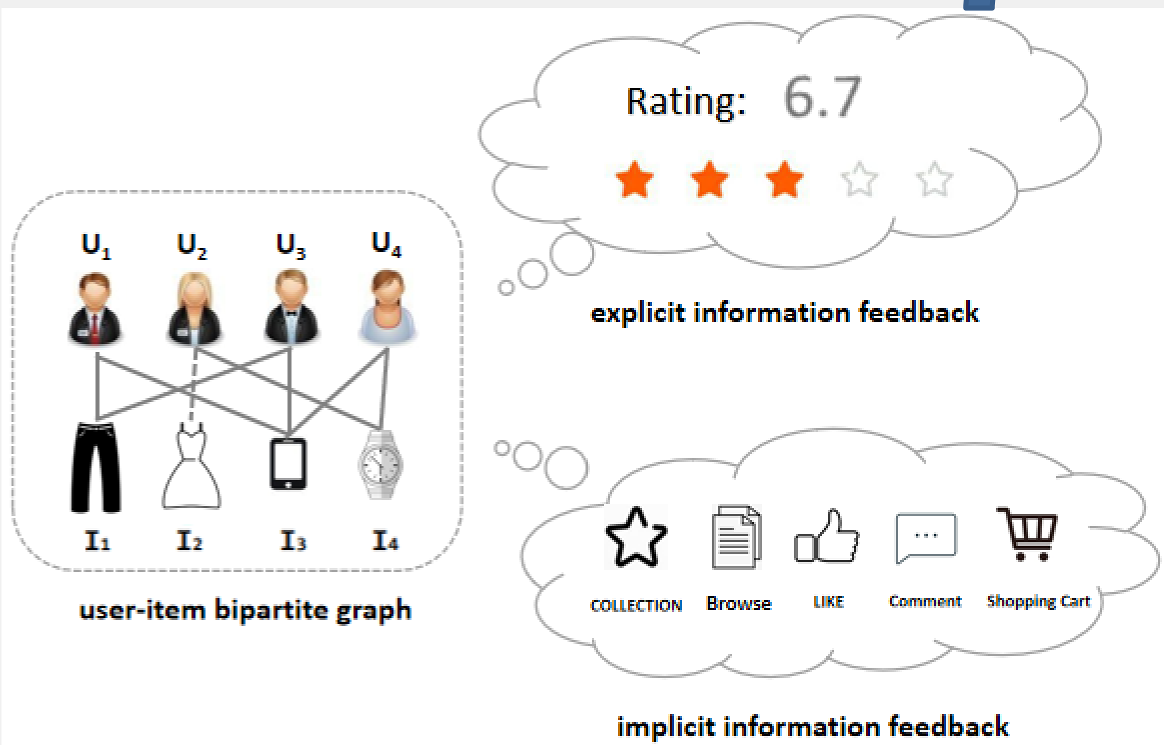
1 Background

Application scenarios

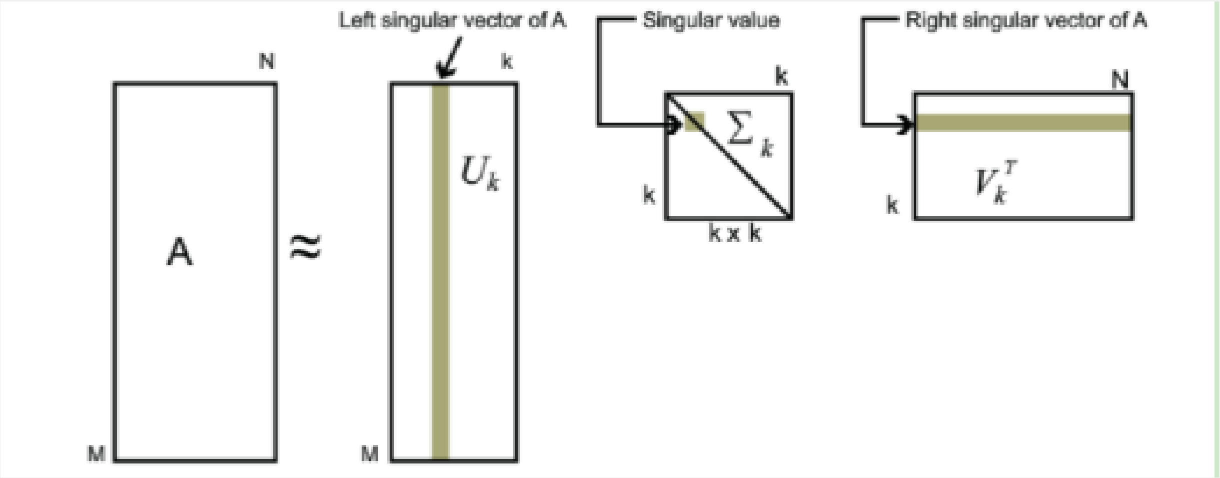


ratings, purchases, friends, follow-ups, and other information that actually happens.

browsing, clicking, collect, comment, adding to the shopping cart, etc.

Explicit Information feedback

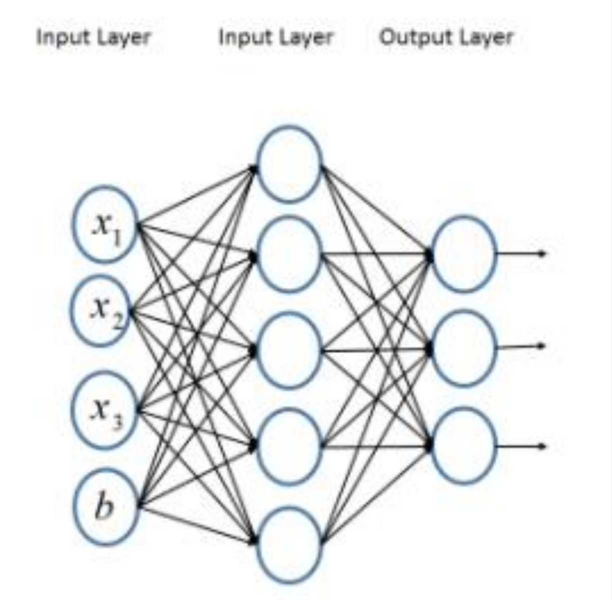
- The core idea of SVD is to decompose the rating matrix into user feature matrix and item feature matrix, and fit the rating matrix by inner product.



$$\hat{r}_{ui} = \mu + b_u + b_i + p_u^T q_i$$

Implicit Information feedback

- Due to the powerful capacity of mining implicit information, deep learning techniques have gained much success in many domains.
  - MLP is a typical deep learning model. In addition to the input and output layers, it can have multiple hidden layers to obtain implicit information feedback.



$$\mathbf{z}^{(l)} = W^{(l)} \cdot \mathbf{a}^{(l-1)} + \mathbf{b}^{(l)},$$

$$\mathbf{a}^{(l)} = f_l(\mathbf{z}^{(l)}).$$

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Problem

Explicit Information Feedback

Implicit Information Feedback

Pros:

High accuracy and pertinence

Cons:

Explicit feedback data is difficult to obtain, and few users are willing to explicitly rate items or express their liking.

Pros:

the data is abundant and easily accessible

Cons:

There is often a lot of noise and a lot of uncertainty in the performance of user interest.

How to fuse those two information granular?

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2 HGAR: Method

PROBLEM DEFINITION

$\{x_1, x_2, x_3, \ldots, x_n\}$:
interactive information attribute
$X = X_1+X_2$:
X contains explicit information granule(X_1) and implicit information granule(X_2)

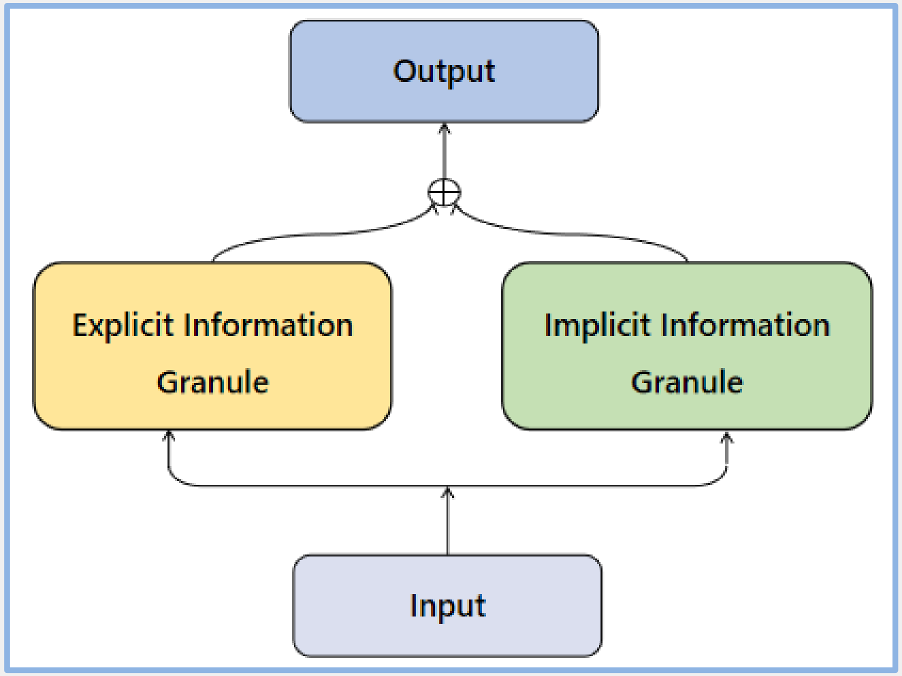
$x_i \in X_j, i \in \{1, 2, 3, \ldots, n\}, j \in \{1, 2\}$:
interactive information attribute is classified into explicit and implicit

Y:the domain of the rating values

f : X → Y: a property function

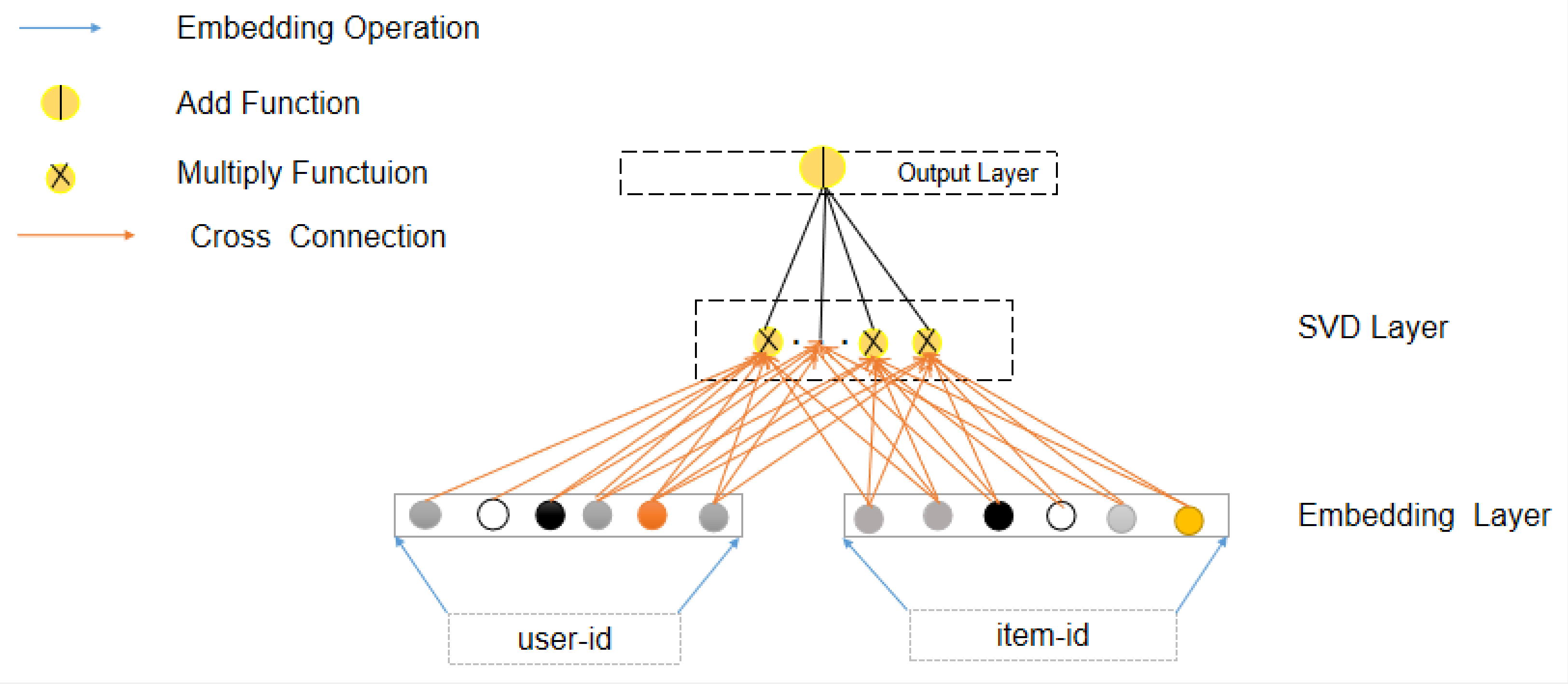
$\{X_{j\}}$ is a partition of X.
the explicit information granule can be defined as： $X_1 = f_{explicit}\ (x_i)$,$Y = f\ (X_1)$;
the implicit information granule can be defined as： $X_2 = f_{implicit}\ (x_i)$,$Y = f\ (X_2)$.
the final output Y is defined as: $Y = f\ (x_1) + f\ (x_2)$.

PROBLEM DEFINITION



HGAR is defined as: $X_j = \{x_i | f(x_i) \in Y\}, i \in \{1, 2, 3, \ldots, n\}, j \in \{1, 2\}$

HGAR:Explicit Information Granule



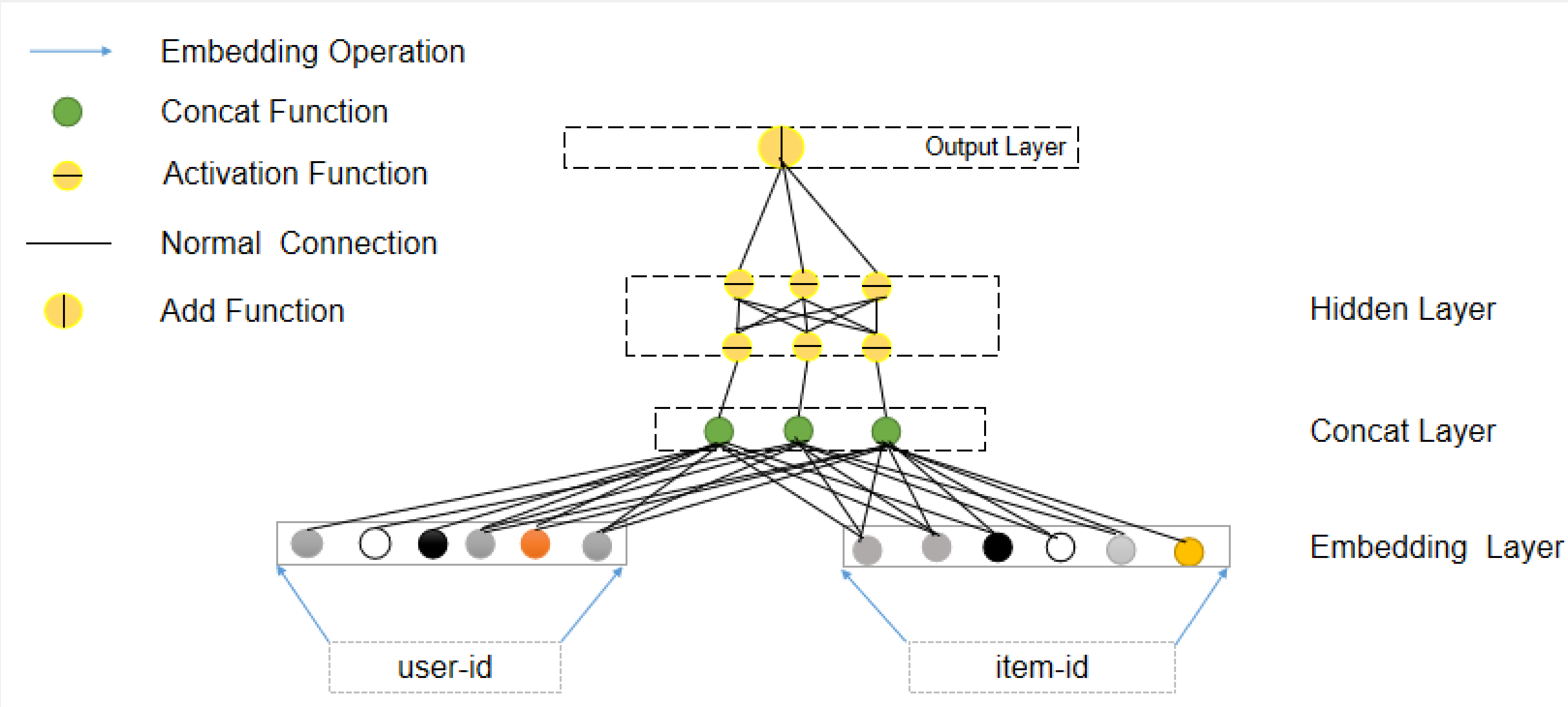
- The user's rating of the item by obtained the explicit information:

$$X_1 = f_{explicit}(uemb, iemb)$$

- The output of the SVD layer:

$$\hat{r}_{ui} = \mu + b_i + b_u + X_1$$

HGAR:Implicit Information Granule



- Concatenate uemb and iemb into one vector:

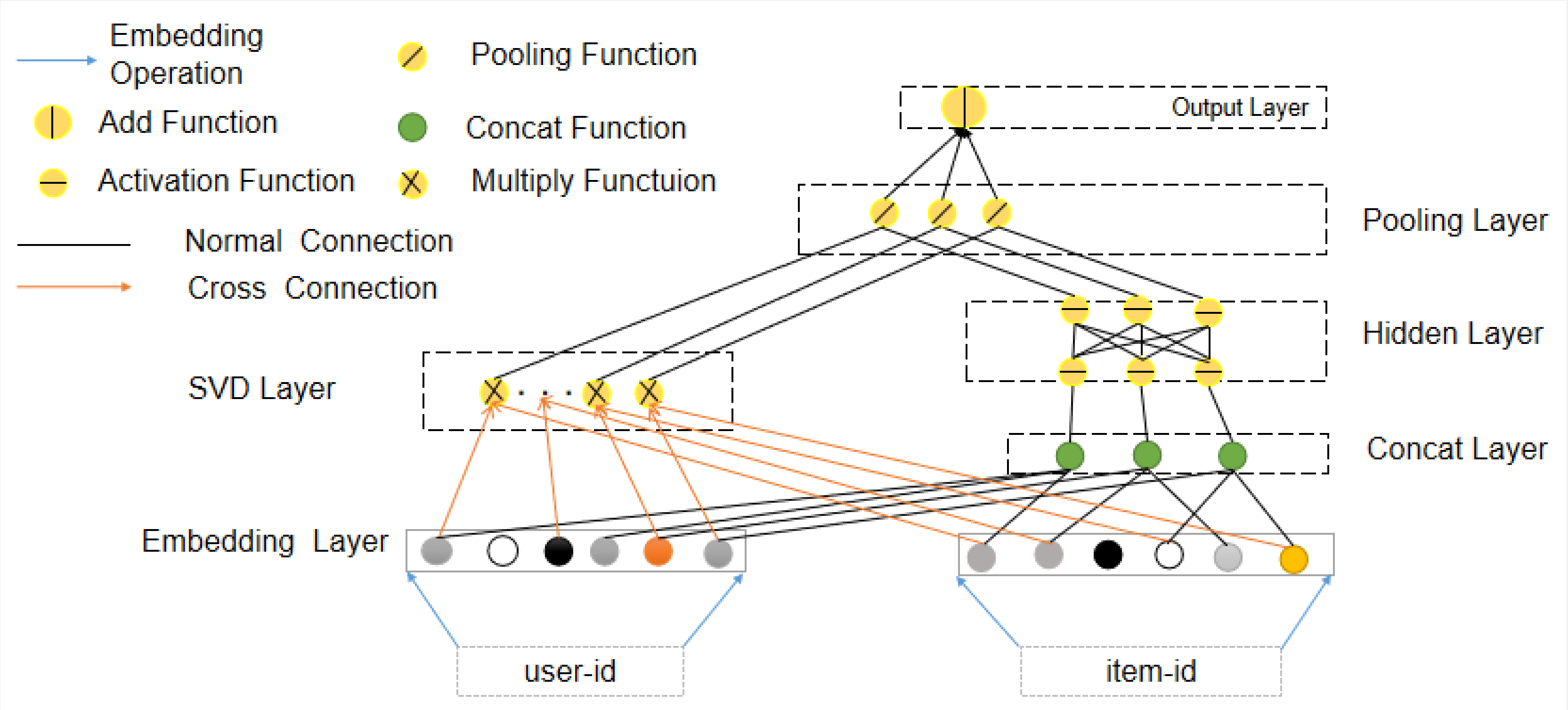
$$\alpha = uemb \oplus iemb$$

- According to the definition of implicit information particles, the hidden layer denotes as:

$$X_2 = f_{implicit}\left(W^{(l+1)}\alpha^l + b^l\right)$$

$$\alpha^{l+1} = f\left(X_2\right)$$

HGAR: Hybrid Granular Algorithm for Rating Recommendation



- Convert ratings with sum pooling to descend to 1-dimension:

$$m = \sum_{i}^{n} e_i, \forall i = 2,3,\ldots,n$$

- The output after fusion is formulated as:

$$\hat{R}_{u,i} = f\left(m_{ui}^{SVD}, m_{ui}^{MLP}\right)$$

3 Experiment

Experiment Settings

Data Sets:

Table 1. Statistics of the MovieLens datasets

	MovieLens 100k	MovieLens 1M
Users	943	6,040
Items	1,682	3,952
Ratings	100,000	1,000,209
Ratings of per user	106.4	165.6
Rating of per item	59.5	253.1
Rating Sparsity	93.7%	95.8%

Evaluation Protocols：

$$MAE = \frac{\sum_{(u,i)\in N} \left| R_{u,i} - \hat{R}_{u,i} \right|}{|N|}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{(u,i)\in N} \left(R_{u,i} - \hat{R}_{u,i} \right)^2}{|N|}}$$

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Baselines

Categories	Methods
explicit information feedback-based	PMF
	BPMF
	RLMC
	RegSVD
	PRMF
	TWDA
implicit information feedback-based	PRA
	CDAE
	SR^{imp}
	SVD++
	Wide and Deep
	Hybird IC-CRBMF
	HACF

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Experimental Results

Table 2. Experimental Performance MAE metrics of HGAR compared to explicit feedback baselines on the MovieLens datasets.

	MovieLens 100k	MovieLens 1M
PMF	0.782	0.690
BPMF	0.881	0.680
RLMC	0.760	0.736
RegSVD	0.733	0.698
PRMF	0.721	0.673
TWDA	0.717	0.670
HGAR	0.717	0.668

- HGAR outperforms all other methods based on explicit information feedback.
- The results reveal that other methods only based on explicit feedback cannot obtain higher precision.

Experimental Results

Table 3. Experimental Performance MAE metrics of HGAR compared to implicit feedback baselines on the MovieLens datasets.

	MovieLens 100k	MovieLens 1M
PRA	0.759	0.714
CDAE	0.735	0.691
SR^{imp}	0.729	0.674
SVD++	0.726	0.668
Wide and Deep	0.723	0.671
Hybird IC-CRBMF	0.719	0.681
HACF	0.717	0.681
HGAR	0.717	0.668

- HGAR achieves the best performance in general and obtained improvements over the implicit-based methods.
- In particular, the result of HACF on Movielens-100k is the same as HGAR, but on the 1M dataset, our result is better.

Only Explicit v.s. Only Implicit

Table 4. Experimental Performance of SVD and MLP on the MovieLens datasets.

Dataset	Movielens 100k		Movielens 1M	
	MAE	RMSE	MAE	RMSE
SVD	0.718	0.916	0.673	0.861
MLP	0.741	0.947	0.716	0.910
HGAR	0.717	0.921	0.668	0.856

- HGAR makes significant improvements compared to the MLP whatever MAE or RMSE on Movielens-100k or 1M.
- Compared to SVD, the RMSE and MAE values of HGAR show good results in Movielens 1M.

4 Conclution

Conclution

- Based on granulation computing, we propose a Hybrid Granular Algorithm for Rating Recommendation (HGAR) to explore the multi-granularity of interaction information for both explicit and implicit feedback.

- We used SVD model to get explicit information and MLP model to obtain implicit information. In addition, we fused the two part information when the two models are jointly trained.

- We conduct extensive experiment on two Movielens datasets to demonstrate the effectiveness and rationality of the proposed HGAR model.

Future work

- Under the framework of HGAR, SVD and MLP in the explicit and implicit information granule are replaced by other methods that conform to the properties of the granule.

- Consider adding attention mechanisms to HGAR for more fine-grained recommendations

- Try experimenting with HGAR on other (larger and more diverse) data sets.

T H A N K