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Paper 20017:

Improving DMF with Hybrid Loss Function and Applying CF-NADE to The MOOC Recommendation System

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2. Deep matrix factorization model (DMF)
3. Hybrid Deep matrix factorization model (Hybrid-DMF)
4. Neural Autoregressive Distribution Estimator for Collaborative Filtering (CF-NADE)
5. Experiment
6. Conclusion and Future works

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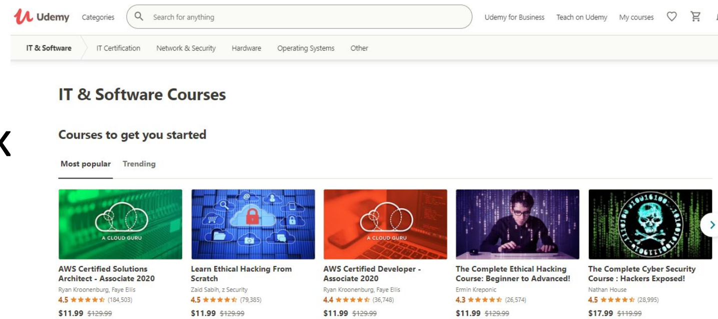
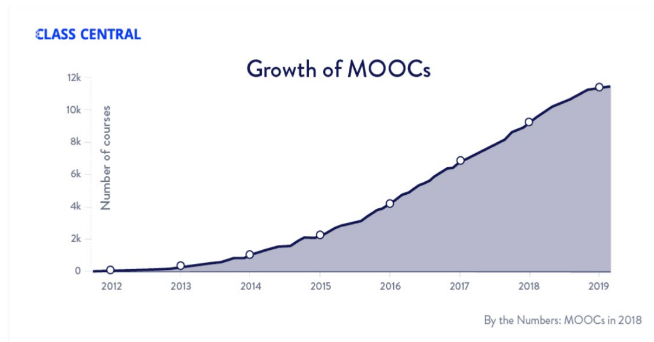
Motivation

- There are many MOOC platforms like Coursera, Edx Udemy, etc.,with millions courses.
- These MOOC plaform attracts hundred millions learners.

→ How to recommend users to choose the appropriate course.





From https://www.classcentral.com

Motivation

- There are few works about MOOC Recommendation system using deep learning.
- Neural Autoregressive Distribution Estimator for Collaborative Filtering(CF-NADE) and Deep Matrix Factorization (DMF) have not been used in Recommendation system.

→ Apply the CF-NADE and DMF model with the improved loss function to the MOOCs suggestion.

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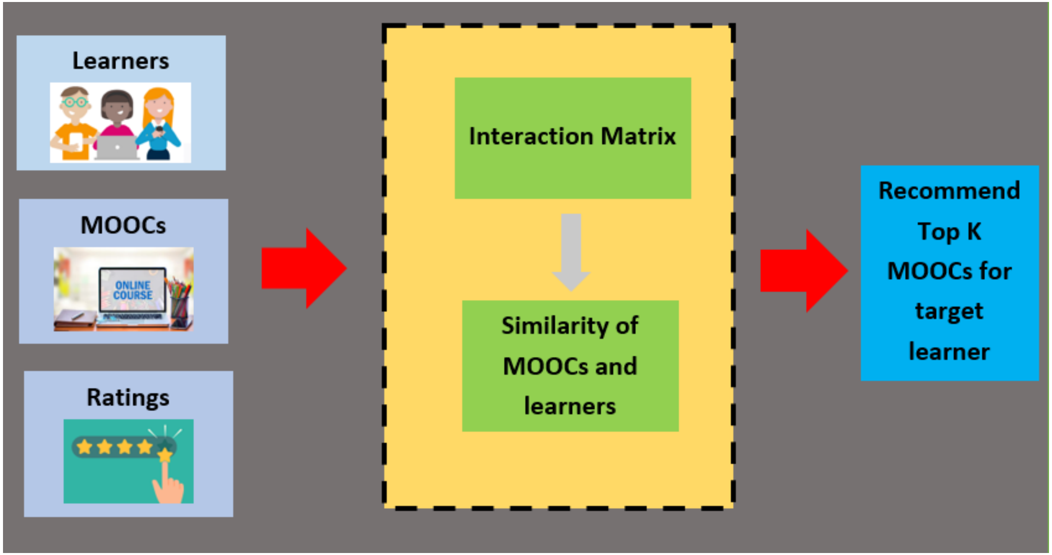
MOOC Recommendation with Deep Matrix Factorization

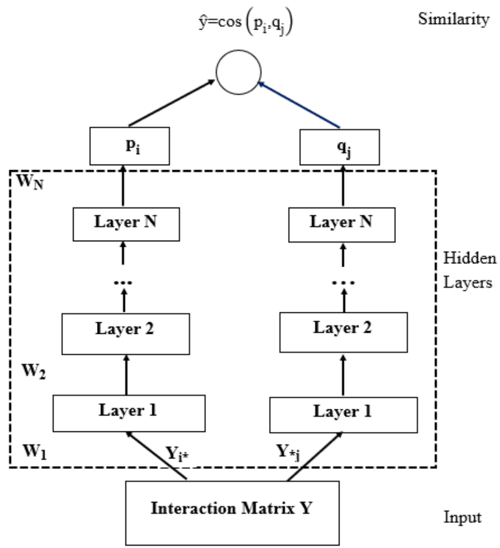


Notation

DMF is proposed by Xue et al., 2017 [1].

Assume:

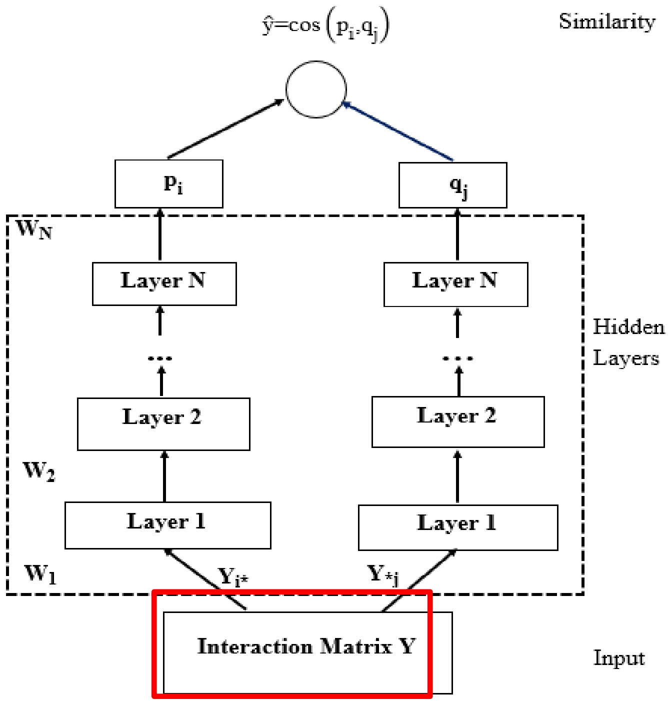
- Set U includes M users: **$U=\{u_1,u_2,\ldots,u_M\}$**.
- Set V includes N items: **$V=\{v_1,v_2,\ldots,v_N\}$**.
- **$R \in \mathbb{R}^{MxN}$** is the rating matrix with **R_{ij}** is rating of user **i** for item **j**, **unk** is unknown rating.
- **i**, **j** is the user and item in **U**, **V**



Interaction matrix

Rating interaction matrix.

$$Y_{ij}=\begin{cases} 0, \text{ if } \mathbf{R_{ij}}=\text{unk} \\ \mathbf{R_{ij}}, \text{ otherwise} \end{cases}$$



Hidden Layers

- Row **i** of matrix **Y** is $\mathbf{Y_{i*}}$, column **j** of the matrix is $\mathbf{Y_{*j}}$.

  This model has two MLPs, one for users and one for items.
- Multi-layer perceptron (MLP) uses.

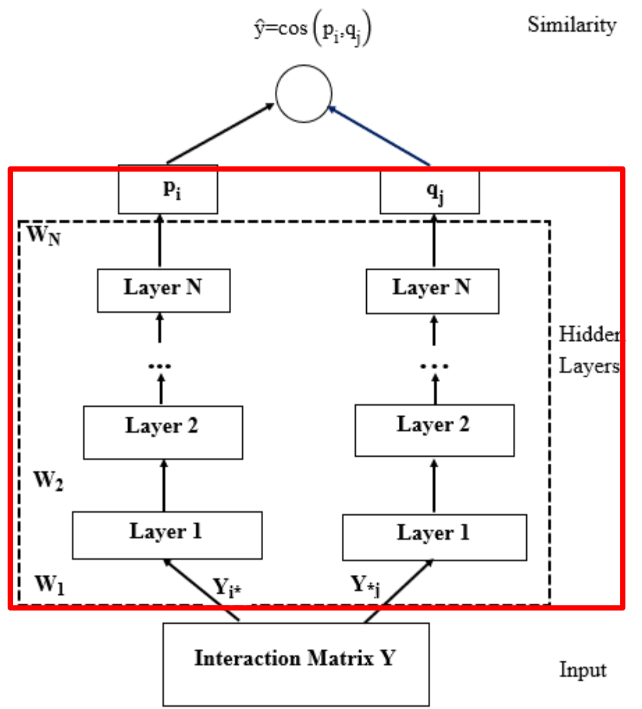
$$l_1 = W_1 x$$

$$l_i = f(W_{i-1} l_{i-1} + b_i);\ i=2,\ldots N-1$$

$$y = f(W_N l_{N-1} + b_N)$$

- The activation function is ReLU.

$$f(x) = \max(0,x)$$

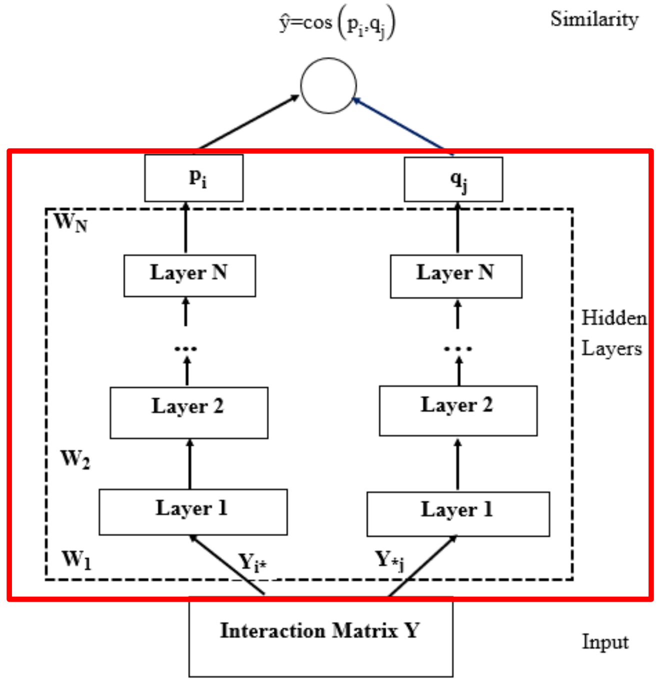


Hidden Layers

In other words, the user and item vector are mapped into low dimensional vectors in latent space using two MLPs.

$$p_i = f_{\theta_N^U}\left(\cdots f_{\theta_3^U}\left(W_{U2} f_{\theta_2^U}\left(Y_{i*} W_{U1}\right)\right)\cdots\right)$$

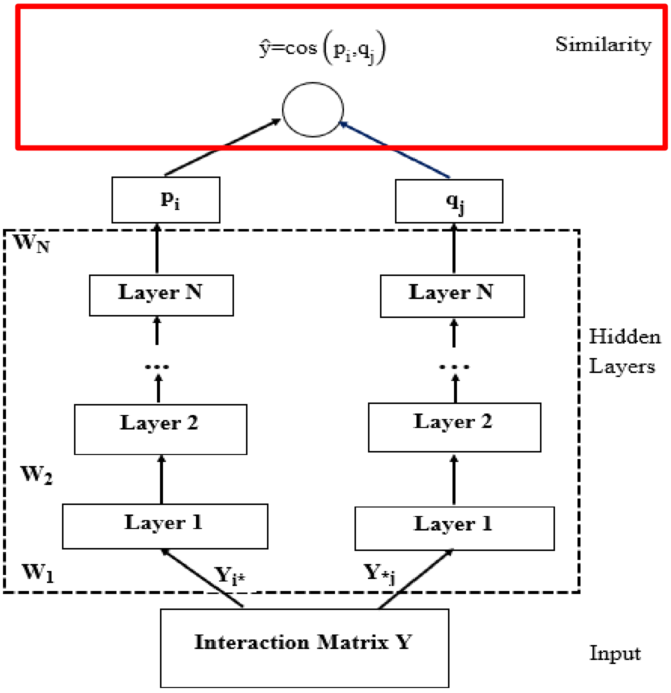
$$q_j = f_{\theta_N^I}\left(\cdots f_{\theta_3^I}\left(W_{V2} f_{\theta_2^I}\left(Y_{*j}^T W_{V1}\right)\right)\cdots\right)$$



Cosine similarity

Then, we calculate the cosine similarity of two latent representations p_i and q_j.

$$\text{cosine}\left(p_i, q_j\right) = \frac{p_i^T . q_j}{\|p_i\| . \|q_j\|}$$



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Normalized cross-entropy loss function

- Normalized cross-entropy loss function (NCE) combines cross-entropy and max rating [1]:

$$L_{NCE} = -\sum_{(i,j)\in Y} \left(\frac{Y_{ij}}{\mathbf{max}(\mathbf{Rating})} \log \widehat{Y}_{ij} + \left(1 - \frac{Y_{ij}}{\mathbf{max}(\mathbf{Rating})}\right) \log\left(1-\widehat{Y}_{ij}\right) \right)$$

- $\frac{Y_{ij}}{\max(\text{Rating})} \in [0;1]$, so it is called Normalized cross-entropy (NCE)
- In our experiment, we use max(Rating) = 5 because 5 is the max rating.

L2 loss function

- L2 loss function fits in solving the overfitting problem.

$$L2 = \frac{\sum_i^m w_i^2}{2}$$

Where:

- $w_i^2 = \sum_j^N w_{ij}^2$, and w_{ij} is the weight of the training instance (i,j);

- N is the dimension of w_{ij}

Hybrid loss function

- Hybrid loss function combines Normalized cross-entropy loss function and L2 loss function.
- Hybrid loss function:

$$L = -\underbrace{\sum_{(i,j)\in Y^{+}\cup Y^{-}} \left(\frac{Y_{ij}}{\max(\text{Rating})}\log\hat{Y}_{ij} + \left(1-\frac{Y_{ij}}{\max(\text{Rating})}\right)\log\left(1-\hat{Y}_{ij}\right)\right)}_{L_{NCE}} + \beta.\underbrace{\frac{\sum_{i}^{M}\sum_{j}^{N} w_{ij}^{2}}{2}}_{L2}$$

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Notation

- CF-NADE is proposed by Zheng et al., 2016 [2].
- **Assuming:**

- There are M courses and N users, the user ratings are from 1 to K.
- Each user rated D courses and $D \ll M$. With any user u, we will have the rating vector $r^u = \left(r^u_{m_{o_1}}, r^u_{m_{o_2}}, \ldots, r^u_{m_{o_D}}\right)$, where o is the permutation of (1, 2, …, D), $r^u_{m_{o_i}} \in \{1,2,\ldots,K\}$ is present for the rating of user u and item m_{o_i}.

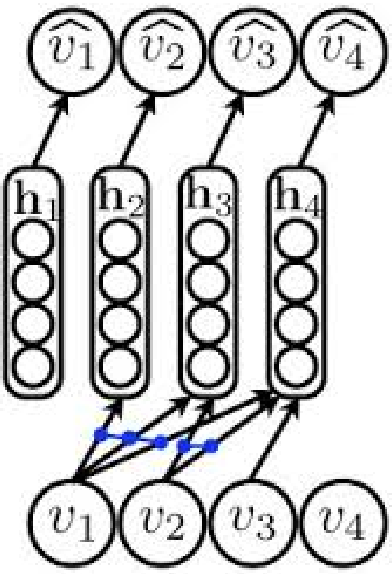
CF-NADE basic model (NADE)

- The probability of the rating vector

$$p(\mathbf{r}) = \prod_{i=1}^{D} p\left(r_{m_{o_i}} \middle| r_{m_{o_{<i}}}\right)$$

- Hidden presentation in a hidden layer

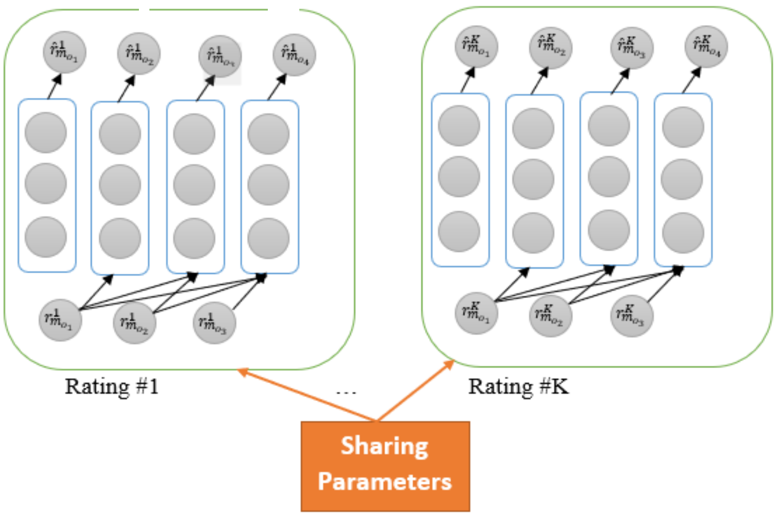
$$h\left(r_{m_{o_{<i}}}\right) = g\left(c + \sum_{j<i} \sum_{k=1}^{r_{m_{o_j}}} W^{k}_{:,m_{o_j}}\right)$$



CF-NADE model with sharing parameters

$$h(r_{mo_{<i}}) = g\left(c + \sum_{j<i} W_{:,\, mo_j}^{r_{mo_j}}\right) \longrightarrow h(r_{mo_{<i}}) = g\left(c + \sum_{j<i} \sum_{k=1}^{r_{mo_j}} W_{:,\, mo_j}^{k}\right)$$

$$s_{mo_i}^{k}(r_{mo_{<i}}) = b_{mo_i}^{k} + V_{mo_j,:}^{k} h(r_{mo_{<i}}) \longrightarrow s_{mo_i}^{k}(r_{mo_{<i}}) = \sum_{j \le k}\left(b_{mo_i}^{j} + V_{mo_i,:}^{j} h(r_{mo_{<i}})\right)$$



Ordinal Cost Function

- Assume that user rates k, then the rating from 1 to k has priority increase, and the value from k to K has priority decrease.

$$p\left(r_{m_{o_i}} = k \middle| r_{m_{o_{<i}}}\right) = \prod_{j=k}^{1} \frac{\exp\left(s_{m_{o_i}}^{j}\right)}{\sum_{t=1}^{j} \exp\left(s_{m_{o_i}}^{t}\right)} \prod_{j=k}^{K} \frac{\exp\left(s_{m_{o_i}}^{j}\right)}{\sum_{t=j}^{K} \exp\left(s_{m_{o_i}}^{t}\right)}$$

- Cost function:

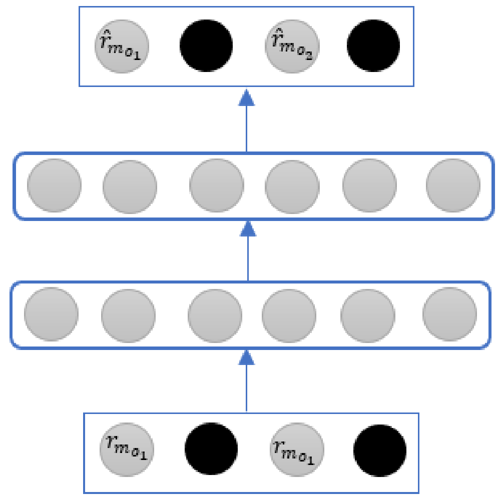
$$C_{hybrid} = (1-\lambda) C_{reg} + \lambda C_{ord}$$

Extend CF-NADE to a deep neural network

- When added a hidden layer to the model, the calculation formula of that layer:

$$h^{(l)}\left(r_{m_{o_{<i}}}\right)=g\left(c^{(l)}+W^{(l)}h^{(l-1)}\left(r_{m_{o_{<i}}}\right)\right)$$

where $l = 2, \ldots, L$ correspond to the hidden layers and the conditional probability $p\left(r_{m_{o_{<i}}}\right)$ is computed based on $h^{(L)}\left(r_{m_{o_{<i}}}\right)$.



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Dataset

- Travel-well dataset [3] is used for our experiment.
- The Travel-well was collected from the LRE portal includes 20 content providers from Europe and elsewhere.
- In our experiment, we only use rating information with 75 learners.

#learners (#users)	#courses (#items)	#ratings	density
75	1608	2156	0.0178

Metric

- ***Normalized Discounted Cumulative Gain*** **(*NDCG*)** evaluate the ranking performance of the relevance courses [4].

$$NDCG@K = Z_K \sum_{k=1}^{K} \frac{2^{r_i} - 1}{\log_2(i+1)}$$

where Z_K is the ideal ranking has a value of 1; r_i is the graded relevance of item at position i.

- **Root mean square error (RMSE)**.

$$RMSE = \sqrt{\frac{\sum_{i,j}^{M,N} \left(r_{ij} - \hat{r}_{ij}\right)}{\#ratings}}$$

Parameter settings

- **Hybrid-DMF, DMF**

+ Hyperparameters: learning rates = 10^{-4}, max epoch = 30, batch size = 256, early stopping = 5, the latent factor = 64.
+ Requirements: python = 3.7.6, Tensorflow-gpu=1.5.0, numpy = 2.1.0.

- **CF-NADE**

+ Hyperparameter: learning rate = 10^{-3}, Hidden unit = 500, epochs = 20.
+ Requirements: Python 3.6.8. Dependence packages: Tensorflow (2.1.0), Tensorflow-gpu (2.1.0), Keras (2.0.8), Pyspark (2.4.1).

Results

We use five algorithms for evaluations (3 classical algorithms and 2 deep learning models):

+ Neighborhood-based collaborative filtering methods on item-based (IBCF) [5]

+ Neighborhood-based collaborative filtering methods on user-based (Pearson correlation) [5].

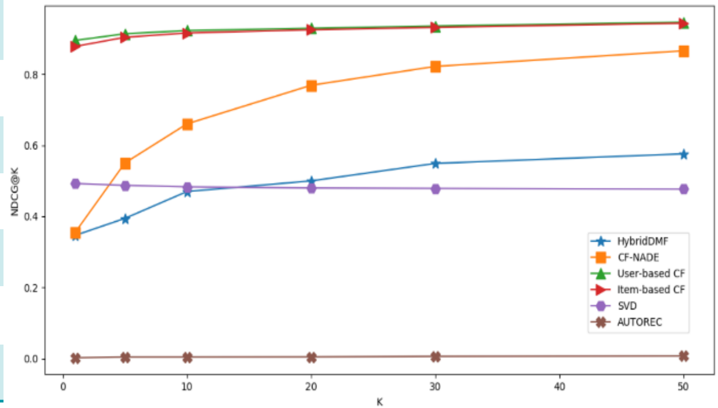
+ Single value decomposition (SVD) [6]

+ Probabilistic Matrix Factorization (PMF) [7]

+ AutoEncoder based on Collaborative Filtering (AutoRec) [8].

Results - NDCG

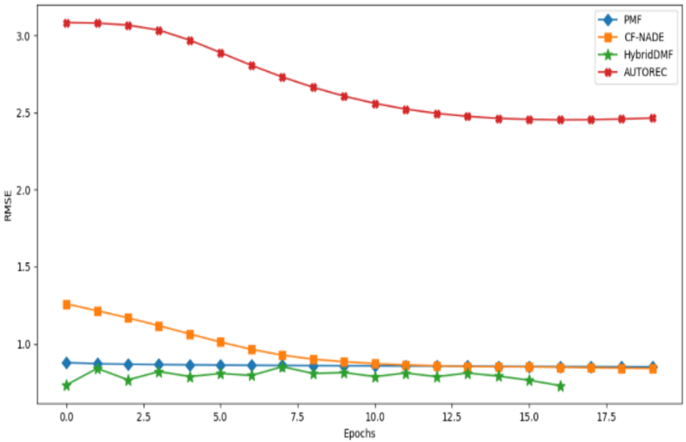
K	Hybrid-DMF	CF-NADE	Auto Rec	SVD
1	**0.3467**	**0.3554**	0.0019	0.4927
5	**0.3945**	**0.5505**	0.0039	0.4875
10	**0.4701**	**0.6606**	0.0040	0.4833
20	**0.5000**	**0.7694**	0.0043	0.4800
30	**0.5493**	**0.8225**	0.0059	0.4789
50	**0.5762**	**0.8665**	0.0070	0.4770



- Detailed results with the NDCG@K metric with K = [1, 5, 10, 20, 30, 50] of the Hybrid-DMF, CF-NADE, AutoRec, SVD, IBCF and UBCF models.

Results - RMSE

Models/Algorithms	RMSE
AutoRec	2.50037
SVD	0.9063
PMF	0.8651
CF-NADE	**0.8283**
Hybrid-DMF	**0.7916**



- Detailed results with the RMSE of the AutoRec, SVD, PMF, Hybrid-DMF, CF-NADE models.
- Hybrid-DMF and CF-NADE gives the best result.

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Conclusion and Future works

- We improved the DMF model with a new loss function (Hybrid-DMF) and combined with the CF-NADE model for the MOOC recommendation system. The results show that the proposed approach is better than the other models with RMSE and NDCG@K measurements when evaluated on the travel-well data set.

- In the future, we will continue to improve DMF with some other loss function and integrate implicit feedback such as the click, tagging, side information. Improving CF-NADE can be done by implicit feedback information, such as user tagging for each course to improve the accuracy of the model.

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Thank you