Enhance Rating Prediction for E-commerce Recommender System using Hybridization SDAE, Attention Mechanism and Matrix Factorization

by Hanafi Hanafi

Submission date: 04-Jun-2022 08:16PM (UTC+0700)
Submission ID: 1850288735
File name: RECSYS-2-IJIES.docx (698.66K)
Word count: 5360
Character count: 31307

Received: January 1, 2017

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Enhance Rating Prediction for E-commerce Recommender System using Hybridization SDAE, Attention Mechanism and Matrix Factorization

Hanafi

[1]*Departement of computer science, Universitas Amikom Yogyakarta, Jl. Ringroad Utara, Condongcatur, Depok, Sleman, Yogyakarta, Indonesia 55283*

* Corresponding author's Email: hanafi@amikom.ac.id

Abstract: E-commerce is essential application in world wide. In everyday live, we cannot escape from e-commerce transaction. E-commerce require intelligent machine to deliver product information to customer. Intelligent machine popular called recommender system developed by matrix factorization. Rating is representation of customer expression for satisfied product or service. Unfortunately, number of rating is too sparse due to majority customer lazy to give rating for e-commerce product. Number of sparse rating matrix have impact in matrix factorization in rating prediction. Moreover, extreme sparse rating have impact degrade performance significantly. Many researcher consider to enhance matrix factorization using customer and product information such as customer demographics information, customer testimony, product review, product description, and etc. In this research, we consider to incorporating stack denoising auto encoder (SDAE), attention mechanism aim to enhance product review document understanding representation and matrix factorization based on probabilistic matric factorization (PMF) to produce rating prediction. According to experiment report, our model superior over previous work based hybridization between PMF and convolutional neural network (CNN), PMF and long short term memory (LSTM), PMF and auto encoder (AE). The effectiveness of our model achieved above 2 in average over best previous work.

Keywords: E-commerce, recommender system, deep learning, matrix factorization, sparse rating, collaborative filtering.

1. Introduction

In two last decade, e-commerce become essential application in world wide. E-commerce famous to recognised with online shopping transaction. In everyday living, we cannot escape for online transaction based on e-commerce for what food to eat, what news to read, what movie to watch, what car to travel, what subject to learn, who people to friend, and etc [1].

Similar with traditional shopping transaction, customer require product information to choose suitable product. E-commerce or online shopping transaction require an engine to provide information for customer of customer candidates. The engine or machine responsible to producing automate information because impossible to produce product fit information manually. E-commerce automatic information engine popular called recommender system or recommendation system [2], [3], [4].

Majority researcher, expert, and academicians believed that successful of e-commerce recommender system influence marketing target. In the other hand, successful of recommender system implementation have impact in e-commerce business corporation revenue. Finally, Adoption of recommender system become important aspect to increase revenue growth of e-commerce company business .

Some research show that recommender system proved in increasing customer deal in many e-commerce company. For example, more than 40% Netflix customer deal with movie recommendation, 60% YouTube users watch video by recommendation, 20% of iTunes revenue obtained by recommendation. This is important reason of

recommender system adoption in many large e-commerce company [5], [2], [6].

There are 4 basic recommender system algorithm included 1. Content based; product recommendation provided based on product behaviour, 2. Demographic based; product recommendation provided based on customer demographic information, 3. Knowledge based, product recommendation serve using knowledge based recommendation, 4. Collaborative filtering, product recommendation provide using customer behaviour in the past [6], [7].

According to several literature review, collaborative filtering become favourite algorithm that adopted in many e-commerce company. Collaborative filtering proved better performance in accuracy over content based. In early collaborative filtering algorithm, adoption of nearest neighbour model become majority approach to develop recommender system such as spearman rank, cosine similarity, adjust cosine similarity. The traditional collaborative filtering also popular called memory based collaborative filtering. However, memory based model face some shortcoming in high computation, require recalculation when any additional user and product information, incompatible to integrated with external information such as product and user information [8], [9].

According to drawback of memory based collaborative filtering mentioned above, in early 2006 rise a mechanism that popular matrix factorization and also popular latent factor model. The matrix factorization aim to handle disadvantage of memory based and increase effectiveness of rating prediction in sparse rating matrix. Matrix factorization has advantage that possible to integrating for side information [10]. Matrix factorization first introduced by Sarwar in early 2000 for rating prediction that popularized with Singular Value Decomposition (SVD) [11]. SVD applied low rank dimensional reduction based on matrix factorization to find correspondents between customer and product relationships. Rating become essential value to find intersection between them. Moreover, index of product for every consumer can be produced specifically following to user personalized. Example of sparse rating matrix show on Figure 1.

A proposed model using PMF and topic modelling aim to increasing effectiveness of rating prediction. Topic modelling is a model to transform of product document using statistical approach to enhance document understanding by Wang [12]. Topic modelling responsible to transform document into word vector that integrated with PMF, while user information transform into 2D latent space using probabilistic mechanism approach. Aims to enhance probabilistic approach, gaussian normal distribution applied in transforming user information. According to their experiment report, hybridization PMF and topic modelling outperform over traditional latent factor that only consider PMF based on RMSE and MAE evaluation metrics.

Figure 1. Minimum rating matrix

A proposed model using PMF and AE aim to increasing effectiveness of rating prediction by Wang [13]. This model is enhancement of topic modelling where the document representation obtained by auto encoder (AE). In the deep learning perspective, AE is variant of deep learning algorithm that involve feature extraction mechanism. PMF responsible to bridging between user information and item document information. While, user information transform into 2D latent space based on Gaussian normal distribution. An enhancement of document understanding using AE success to increase performance of topic modelling based on RMSE evaluation metrics.

A proposed model using PMF and CNN aim to increasing effectiveness of rating prediction by Kim [14]. CNN tried to advance product document understanding. In this research, Kim also applied word embedding application using GLOVE (Global Vector for Word Vector Representation) before process and integrate into CNN machine. While, CNN responsible to transform product document into 2D latent space before compute and hybrid PMF and user information representation that calculate into 2D latent space using Gaussian normal distribution. The enhancement of PMF for rating prediction using GLOVE and CNN success to increase effectiveness of rating prediction. Moreover, CNN outperform over hybridization between PMF and AE. The PMF and CNN model implemented in ML-1M, ML-10M, and Amazon datasets.

Similar with previous work, Hanafi proposed a hybrid model using PMF and deep learning approach based on LSTM [15]–[17]. The objective of this

study to advance product document understanding using LSTM. In this model also applied GLOVE framework to transform product document latent space. The involvement of LSTM aim to calculate of product document with sequential technique. Different with CNN model that consider dimensional reduction technique using convolutional process. LSTM has benefit to capture product document understanding over CNN model due to word order consideration. According to experiment report, hybridization between LSTM and PMF superior over previous work based on topic modelling, AE, CNN with significant performance. Similar with previous work, the PMF and LSTM also applied Gaussian normal distribution to transform user information latent space.

A proposed model based on PMF and dual deep learning model using SDAE and CNN [18]. It was contrast with some previous work, an enhancement user information using SDAE was applied. SDAE responsible to change Gaussian normal distribution for transforming user information latent space. While, PMF and LSTM have similar task with previous work. The hybridization technique is this research popular called PHD (Probabilistic Hybrid Deep Learning). PHD also applied in similar datasets following to previous work using ML-1M, ML-10M, and Amazon datasets. According to experiment report, PHD model success to increase effectiveness of previous achievement based on PMF and CNN. In the other hand, SDAE to transform user information plays important role to enhance effectiveness of rating prediction. Table 1 show some state of the art in collaborative filtering recommender system

A study involve PMF and dual deep learning based on SDAE and LSTM aim to enhance effectiveness of sparse rating matrix by Hanafi [19]. This hybrid model named Dual Deep Learning and PMF (DDL-PMF). Almost similar with previous work, author tried to enhancement PHD model using GLOVE and LSTM and implemented the model in ML-1M, ML-10M and Amazon datasets. According to experiment report, DDL-PMF success to increase performance over PHD model as best previous work. This model was evaluated by root mean squared error (RMSE) and Mean Absolut Error (MAE). Author believe that role of SDAE and LSTM play essential aspect in increasing of effectiveness level in rating prediction task.

A new model proposed in recent year using PMF and Attention mechanism [20], [21]. Attention is essential finding in recent year. It have ability in optimizing deep learning task in computer science field such as text processing, voice recognizing, image processing. In this study, attention approach used to advance document context of product document representation. The adoption of attention mechanism in the study success to increase product document understanding. It was believed the performance of attention mechanism and PMF outperform over best previous work using LSTM and PMF based on RMSE evaluation metrics.

Table 1. State of the art of collaborative filtering recommender system

Ref.	Method	Model based / latent factor		Explicit feedback	Auxiliary information		Deep learning			
		SVD	PMF	Rating	Item side document	User side information	AE	CNN	LSTM	Attention
[22]	PMF	-	√	√	-	-	-	-	-	-
[23]	CTR	-	√	√	√	-	-	-	-	
[13]	CDL	-	√	√	√	-	√	-	-	-
[20]	ATT-PMF	-	√	√	√	-	-	-	√	
[24]	HCDR	√	-	√	√	-	√	-	-	-
[14], [25]–[27]	CNN-PMF	-	√	√	√	-	-	√	-	
[15]–[17]	LSTM-PMF	-	√	√	√	-	-	-	√	-
[18]	PHD-PMF	-	√	√	√	√	√	√	-	
[19]	DDL-PMF	-	-	-	√	√	√	-	√	-
SDAE, Attention, and PMF			√	√	√	√	√	-	-	√

Collaborative filtering still face in several challenge in the future research. The enhancement of side information also popular named auxiliary information required improvement in the term information resources and algorithm enhancement model. Social media information and internet of thing

can be explored. According to description on above, the contribution of this study can be concluded as follow:

- Novel model in hybridization between SDAE to enhance user information representation, Attention mechanism to enhance contextual product document understanding and PMF responsible to generate rating prediction for sparse rating matrix.
- Enhancement of product document understanding using attention mechanism and word embedding using GLOVE.
- Enhance user demographic information representation using feature extraction model based on SDAE.

2. Methodology

The proposed framework that involves SDAE, PMF, Attention, and some pre-processing approach. Deep learning is the novel achievement in machine learning algorithm in 2 last decade. It has success to reach improvement in several computer science research and industry such as image processing field [28], text processing for recommender system [15], [16], [29]–[32] . The detail explanation of experiment scenario explained in this section as follow:

2.1 PMF

PMF is represent latent factor collaborative filtering recommender system. It also popular called model based collaborative filtering. PMF is enhancement of SVD model that responsible to produce rating prediction. The basic work of PMF is suppose we have *M* represent of item and variable *N* as user representation. While, rating value representation start from *1* to *k*. Then, the representation of user *i* for movie *j* can be obtained by R_{ij}. *U* and *V* represents of users and movies latent factor that produced by $U \in R^{D\times N}$ and $V \in R^{D\times M}$. The processing to observed rating value as follow:

$$p(R|U,V,\sigma^2) = \prod_{i-1}^{N}\prod_{j-1}^{M} N\left[(R_{ij}|U_i^T V_j,\sigma^2)\right]^{I_{ij}}$$

Aim to transform 2D latent vector consider to apply Zero mean spherical Gaussian Prior of user as;

$$p(U|\sigma_U^2) = \prod_{i=1}^{N} N(U_i|0,\sigma_U^2 I)$$

While, transforming item representation 2D latent space can be obtain by;

$$p(V|\sigma_V^2) = \prod_{j=1}^{N} N(V_j|0,\sigma_V^2 I)$$

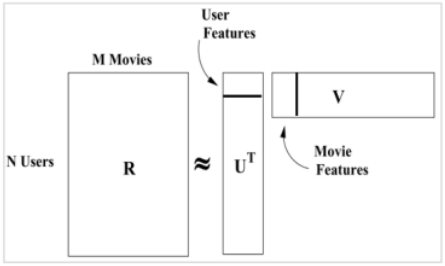


Figure 2. PMF task to produce rating prediction

For the further process, PMF responsible to produce rating prediction will integrated with user and item information with SDAE dan attention mechanism aim to increase effectiveness to generate rating prediction.

2.2 SDAE

SDAE was introduced by Vincent to enhance feature extraction of auto encoder algorithm [33]. It used multiple combination of stacked layer to generate weight representation in hidden layer. Our research adopted PHD model by Liu [18]. They combined two part of users side information. Detail framework of SDAE model can be seen on Figure 3 below.

SDAE work by employ matrix *U* for generating latent factor model. While, process to produce user latent factor can be calculate with equation as follows:

$$h_l = g(C_l h_l + Q_l \tilde{X} + b_l)$$

C_l and Q_l responsible to represent weight parameter of each layer. While b1 consider to eliminate in each layer for bias vector.

$$\hat{R}_i = f(C_L h_L + b_{\hat{R}_i}) \text{ and } \hat{X} = f(Q_L h_L + b_{\hat{X}})$$

Variable Q_l and C_l represent of weight parameter to each session. While b1 responsible to solving the bias vector for each network. Ri represent the corrupt value of h0, variable g() responsible to calculate non linier activation function. Symbol X represent the corrupt value of $\tilde{X}$. While, the output value L can be computed with equation as follow:

$$\hat{R}_i = f(C_L h_L + b_{\hat{R}_i}) \text{ and } \hat{X} = f(Q_L h_L + b_{\hat{X}}) \quad (5)$$

In the second layer of activation function represent as *f*(). While, $\frac{L}{2}$ as represent 2 layer of SDAE where first $\frac{L}{2}$ represent encoder task and second $\frac{L}{2}$ responsible for decoder task.

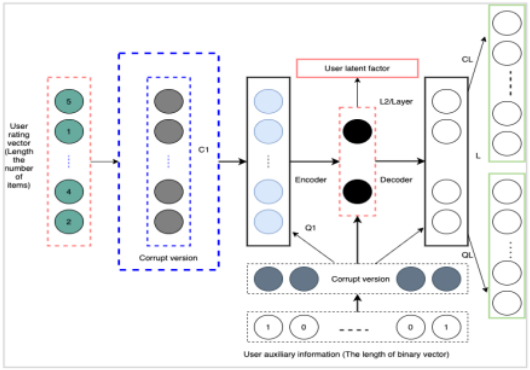


Figure 3. Architecture of SDAE

2.3 Attention

Attention is essential finding is recent year. This method play important role in enhancement of deep learning enhancement work. Attentions mechanism adopt of human mind attention in mimics. In older approach, application in machine learning model including computer vision, language processing involves traditional neural network. However, a new strategy implement seq2seq model was used in majority translation machine. According to basic seq2seq mechanism, the encoder responsible to calculate the incoming data and compresses the data to context vector in the form of fix length (common process named sentence embedding). The second process is decoding step where decoder applied the context vector computation to generate an output that was converted. The shortcoming of seq2seq model solved with tremendous achievement with this architecture. Sentence embedding was produced by one vector that very difficult for an algorithm to compute a length of input data.

Attention mechanism suitable neural machine improvement with remembering technique for long sentence category. Attention mechanism first introduces in recent year [34]. Attention makes a data input, develop one context vector in the beginning process. In every output data, they adjusted the weight of shortcut relation. The process put data that it is not important into the background.

As a result, there are several attention value that was computed for every input. Not for all input are computed to produce the output correspondent. According to the reason, attention machine computes overall attention weight. The weigh sum is developed with objective to employ the context vector (C_i) to produce the output (y_i). The graphic illustration of Attention mechanism work can be seen on Figure 3 below.

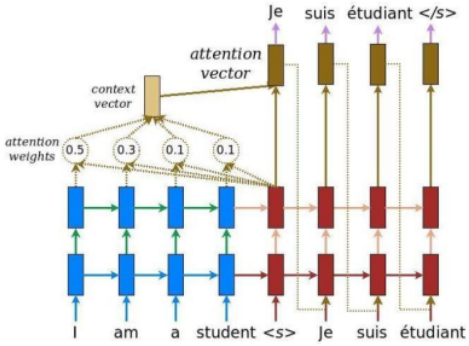


Figure 3. Basic work of attention

While not every input would be applied in producing the output correspondent, the attention algorithm compute every weight signed by $\alpha(t,1), \alpha(t,2), .., \alpha(t, t)$. Aims to generate the weight sum using the context vector with C_l and the output result y_i with the equation as follow:

$$C_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$$

Aim to catch correspondent between an input j and an output i using normalizing feed forward neural network, attention weight were calculated by using SoftMax function to enumerate the weight α_{ij} with the equation as follow:

$$e_{ij} = a(h_j, S_{t-1}), \forall j \in [1, T]$$

$$\alpha_{tj} = \frac{\exp(e_{tj})}{\sum_{k=1}^{T} \exp(e_{tk})}$$

e_{ij} represent the value of the output from feed forward of neural network that acquired from the function aims to capture correspondent among input of j and output of i.

Table 2. Notation of equation

notation & description		notation & description	
U	user representation	V	item representation
σ^2	variance value	ε_i	epsilon variable of item
σ_U^2	variance value of user	σ_V^2	variance value of item
W^+	internal weight	X_i	represent side information of product
R_{ij}	actual value of rating	M	raw of product
N	raw of users	I_i	diagonal matrix
I_{ij}	indicator function	v_j	product of item j
μ	mean value	σ	standard deviation

2.4 Integrating SDAE, Attention and PMF

The basic concept of our proposed model consist of 3 essential algorithm including SDAE, Attention mechanism and PMF. SDAE and attention aims to handling user and item side information, while PMF aims to bridging SDAE and attention in generating rating prediction. The basic work explanation task on above can be calculated with equation:

$$p = (R|U,V,\sigma^2) = \prod_i^N \prod_j^M N(R_{ij}|u_i^T v_j, \sigma^2)^{I_{ij}}$$

In our proposed model, we consider to apply normal distribution $N(x|\mu,\sigma^2)$ as represent pdf (probability density function). SDAE is user representation point of view which is contain 3 important factor. *Xi* as user side information representation for user i, *W+* as internal weight value representation, and varepsilon of Gaussian noise. User latent factor representation can be computed as follow:

$$u_i = sdae(W^+, X_i) + \varepsilon_i$$

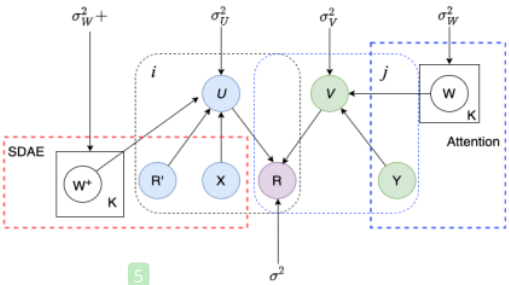
We implemented zero mean spherical Gaussian prior for graphic representation of Gaussian normal distribution.

$$p(w^+|\sigma_{W^+}^2) = \prod_k N(w_k^+|0,\sigma_{W^+}^2)$$

The user latent factor can be calculated with the equation on below, following to probabilistic density function mechanism.

$$p(U|W^+,X,\sigma_U^2) = \prod_i^N N(u_i|sdae(W^+,X_i),\sigma_U^2)$$

Our model consider to applied some probabilistic mechanism of data dimensional transformation. The detail explanation of data distribution and integration between SDAE, Attention and PMF according to probabilistic point of view can be explained on Figure 5 below.



R : symbol of rating matrix
R' : actual rating matrix
X : user extra information
Y : item extra information

Figure 4. Illustration of probabilistic hybridization process and schematic data transformation

2.5 Datasets

Our research consider to applied in real datasets and most popular research in e-commerce recommender system. The datasets consist of two categories, MovieLens ML.1M and ML.10M as rating representation and Amazon as product review document representation. ML.1M contain 1 millions of rating and 10 millions of rating. The complete characteristic and feature of the datasets can be seen on Table 3 below. The objective our datasets implementation in our model to observe the ability in handling sparse rating matrix problem.

Table 3. Datasets characteristic

Dataset category	User side information	Item side information	Number of users	Number of items	Number of ratings	Sparse level (%)
ML-1M	Gender / age / occupation / zip code	Movie descriptions	6,040	3,544	993,482	1,413%
ML-10M	Tags application	Movie descriptions	69,878	10,073	9,945,875	4.641%
Amazon	Demographic characteristics	Movie review	81,339	18,203	238,352	0.016%

2.6 Evaluation metrics used RMSE

Aims to observe the effectiveness of our model, we evaluate using RMSE evaluation metrics. We split the dataset into data training and data testing with 10% interval sparseness level of rating, where 10% data training and 90% data testing are categorised into highest sparseness level and vice versa. The formula of RMSE to evaluated of rating prediction result can be calculated with equation as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i,j} Z_{i,j}^{P}(R_{ij} - \hat{R}_{ij})^2}$$

Where, N variable represents the total number of ratings, while $Z_{i,j}^{P}$ represents the test rating. It means the actual value of rating from datasets compared with rating value from prediction result.

3. Result and discussion

Sparsity is serious problem in many computer science territory. In e-commerce recommender system, sparsity problem due to minimum number of rating also become major issue. This study consider to enhance sparse problem with enhance user and item information with SDAE, Attention, and PMF. The experiment aims to observed the effectiveness of our model that was described on below.

First experiment session, we divided ML.1M into 10% data training and 90% data testing. It categorical highly sparse level due to only 10% data for learning mechanism, while 90% data for testing mechanism. In the second process, we conduct similar schema with 10% interval of additional data training and reducing data testing with 10% interval also until last experiment scenario in the eight session.

Our experiment scenario aims to observe the effectiveness of our model with attention mechanism to capture product document context from review, where document context with W expect to increase share weigh of product document representation. Finally, according to experiment report on Table 4, our model outperform over previous work that involve CNN and LSTM model in capturing of document context. While, according to user information representation in PHD and DDL-PMF, they used similar algorithm based on SDAE. In the other hand, it can be concluded that role of Attention mechanism very important to increase share weight W in product document representation. ML.1M MovieLens categorical sparse datasets where the number of rating only 1,41%. However, the performance of SDAE, Attention and PMF achieved better performance over best previous work using PMF and SDAE-LSTM-PMF.

Table 4. RMSE Comparison result on ML.1M

Ratio	Collaborative Filtering Hybrid Model			
	PMF	PHD-PMF	DDL-PMF	SDAE-ATT-PMF
10%	1,64697	0,98684	0,96298	**0,94787**
20%	1,26577	0,94889	0,93392	**0,91881**
30%	1,11180	0,93053	0,90986	**0,89475**
40%	1,03992	0,91326	0,89842	**0,88331**
50%	0,99064	0,89819	0,89371	**0,87859**
60%	0,95897	0,88936	0,88095	**0,86584**
70%	0,93369	0,88146	0,87272	**0,85761**
80%	0,91134	0,87237	0,86605	**0,85139**
90%	0,90452	0,86919	0,85837	**0,84315**
∑				
X̄				

The second experiment, we applied our model in ML.10M datasets which is categorical huge datasets. The result of our experiment and comparison show that role of SDAE and attention to support PMF in rating prediction is very essential. SDAE responsible to extract user information representation in the term of tags application to enhance of internal user share weight W^{+} representation, and item share weight W representation. The share weight value obtain by Attention mechanism more representation with seq2seq aspect over CNN and LTSM. Table 4 show that our proposed model achieve better performance in effectiveness with significantly performance.

Table 5. RMSE Comparison result on ML.10M

Ratio (%)	Collaborative Filtering Hybrid Model			
	PMF	PHD-PMF	DDL-PMF	SDAE-LSTM-PMF
10%	1.27539	1.17821	**1.32981**	1.37942
20%	1.05233	0.83530	0.90216	**0.90068**
30%	0.96513	0.81901	0.80812	**0.798412**
40%	0.91827	0.80651	0.79945	**0.785681**
50%	0.88834	0.79962	0.78819	**0.779172**
60%	0.86673	0.79220	0.78134	**0.770198**
70%	0.85071	0.78252	0.77681	**0.764091**
80%	0.84055	0.77991	0.76145	**0.755189**
90%	0.82796	0.76186	0.75998	**0.749038**
∑ (Total)				
X̄ (Average)				

Aim to observe the performance of our model in achieving convergence value for training process, we evaluated using curve illustration, where blue colour

represent of PMF training result, orange colour represent of DDL-PMF and green colour represent of SDAE, attention and PMF. The detail of training process can be seen on Figure 5.

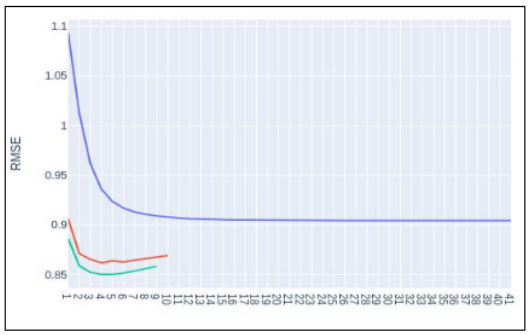


Figure 5. Graphic RMSE evaluation result and impact of attention

PMF as traditional latent factor collaborative filtering reach low accuracy and high computation to learn process because of only consider rating matrix factor to generate rating prediction. While, Orange colour that represent SDAE-LSTM-PMF achieve better performance significantly over PMF. Certainly, it was influenced by side information impact for user information representation in U that support by share weight W^+ and also item share weight W. In this research, internal item share weight was enhancement using seq2seq aspect. It was influence in effectiveness and reduce the computation cost in rating prediction learning process.

The second experiment involves some hybridization essential collaborative filtering algorithm aim to observe seq2seq aspect of attention in capturing product review and SDAE as user information where green colour as PMF model, blue colour as CNN and PMF model, orange colour as LSTM and PMF model, red colour as hybridization between SDAE, LSTM and PMF model, and purple colour as hybridization between SDAE, Attention and PMF.

According to RMSE evaluation result in the term of curve illustration Figure 6 can be observe that the model involving item information representation only (blue and orange) achieved better performance over PMF. In the other hand, they only consider W as internal item share weight. However, the training process to reach convergence required high computation and repeat much more over the model that involve both user and item information representation (red and purple).

The different approached by DDL-PMF (SDAE, LSTM and PMF) and SDAE, Attention and PMF where they consider to adopt both of information to support PMF task. According to experiment result show on figure below, they achieved low computation. Both of them reach convergence quickly. Moreover, they reach better performance in effectiveness over previous work. We believed that the effectiveness of both model due to enhancement of user and item information by SDAE and attention mechanism that applies seq2seq aspect to produce internal share weight W and W^+ to support U as user representation and V as item representation.

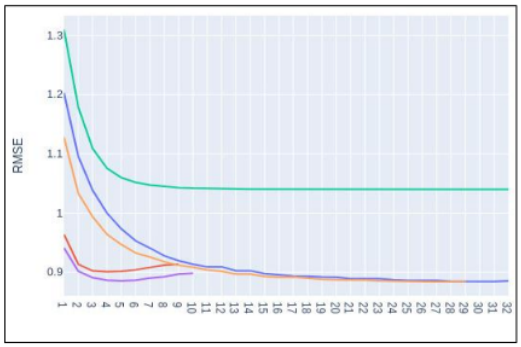


Figure 6. Graphic RMSE evaluation result and effect of SDAE and Attention

4. Conclusion

In this study, we adopt attention mechanism to enhance collaborative filtering based on model based by enhancement product document information using attention mechanism. Attention mechanism success to enhance product document representation that applied CNN and LSTM in previous work. Attention mechanism consider to implement sequence to sequence aspect. In the other hand, seq2seq aspect success to enhance product document understanding context.

Our experiment demonstrated the involvement of attention mechanism suitable to adopt in huge datasets and success to increase effectiveness of rating prediction. Moreover, our model also achieve in low repetition to achieve training convergence. We believe that involving item and user information representation become essential factor in performance result.

For the future, involvement user and item side information will become essential factor to handle sparse data problem. Social media information is promising information that will be integrated into collaborative filtering based on model based. Social

media information can be generated easily. The challenge in the future is how to integrated and selected relevant information that adequate to adopt in recommender system.

Conflicts of Interest

The authors declare no conflict of interest on this study, authorship and publishing of this manuscript on this research.

Acknowledgments

This work was supported by Universitas Amikom Yogyakarta

References

[1] Hanafi, R. Widyawati, and A. S. Widowati, "Effect of service quality and online servicescape toward customer satisfaction and loyalty mediated by perceived value," in IOP Conference Series: Earth and Environmental Science, 2021, vol. 704, no. 1. doi: 10.1088/1755-1315/704/1/012011.

[2] J. A. Konstan and J. Riedl, "Recommender systems : from algorithms to user experience," pp. 101–123, 2012, doi: 10.1007/s11257-011-9112-x.

[3] Hanafi, N. Suryana, and A. Sammad, "An Understanding and Approach Solution for Cold Start Problem Associated with Recommender System : A Literature Review," J Theor Appl Inf Technol, vol. 96, no. 09, pp. 2677–2695, 2018.

[4] Hanafi, N. Suryana, and A. S. B. H. Basari, "Paper Survey and Example of Collaborative Filtering Implementation in Recommender System," J Theor Appl Inf Technol, vol. 95, no. 16, 2017.

[5] Hanafi, N. Suryana, and A. Samad, "Deep Learning for Recommender System Based on Application Domain Classification Perspective : a Review," J Theor Appl Inf Technol, vol. 96, no. 14, pp. 4513–4529, 2018.

[6] J. Bobadilla, F. Ortega, A. Hernando, and A. Gutiérrez, "Recommender systems survey," Knowledge-Based Systems, vol. 46, pp. 109–132, 2013, doi: 10.1016/j.knosys.2013.03.012.

[7] W. Carrer-Neto, M. L. Hernández-Alcaraz, R. Valencia-García, and F. García-Sánchez, "Social knowledge-based recommender system. Application to the movies domain," Expert Systems with Applications, vol. 39, no. 12, pp. 10990–11000, 2012, doi: 10.1016/j.eswa.2012.03.025.

[8] F. Ricci, L. Rokach, and B. Shapira, Recommender Systems Handbook, 2nd ed. London: Springer New York Heidelberg Dordrecht London, 2015. doi: 10.1007/978-0-387-85820-3.

[9] C. C. Aggarwal, Recommender systems: The Textbook. London: Springer International Publishing Switzerland, 2016. doi: 10.1007/978-3-319-29659-3.

[10] Y. Koren, R. Bell, and C. Volinsky, "Matrix Factorization Techniques for Recommender Systems," IEEE, vol. 40, no. 8, pp. 42–49, 2009.

[11] B. M. Sarwar, G. Karypis, J. a Konstan, and J. T. Riedl, "Application of Dimensionality Reduction in Recommender System - A Case Study," Architecture, vol. 1625, pp. 264–8, 2000, doi: 10.1.1.38.744.

[12] S. Purushotham, Y. Liu, and C.-C. J. Kuo, "Collaborative Topic Regression with Social Matrix Factorization for Recommendation Systems," 2012. doi: 10.1016/j.nimb.2008.03.150.

[13] H. Wang, N. Wang, and D.-Y. Yeung, "Collaborative Deep Learning for Recommender Systems," 2015. doi: 10.1145/2783258.2783273.

[14] D. Kim, C. Park, J. Oh, S. Lee, and H. Yu, "Convolutional Matrix Factorization for Document Context-Aware Recommendation," pp. 233–240, 2016, doi: 10.1145/2959100.2959165.

[15] Hanafi, N. Suryana, and A. S. H. Basari, "Generate Contextual Insight of Product Review Using Deep LSTM and Word Embedding," Journal of Physics: Conference Series, vol. 1577, no. 1, 2020, doi: 10.1088/1742-6596/1577/1/012006.

[16] Hanafi, N. Suryana, and A. S. H. Basari, "Deep Contextual of Document Using Deep LSTM Meet Matrix Factorization to Handle Sparse Data: Proposed Model," Journal of Physics: Conference Series, vol. 1577, no. 1, 2020, doi: 10.1088/1742-6596/1577/1/012002.

[17] Hanafi and B. M. Aboobaider, “Word Sequential Using Deep LSTM and Matrix Factorization to Handle Rating Sparse Data for E-Commerce Recommender System,” Computational Intelligence and Neuroscience, vol. 2021, no. 1, 2021, doi: https://doi.org/10.1155/2021/8751173 Research.

[18] J. Liu and D. Wang, “PHD : A Probabilistic Model of Hybrid Deep Collaborative Filtering for Recommender Systems,” in ACML, 2017, pp. 224–239.

[19] Hanafi et al., “Handling Sparse Rating Matrix for E-commerce Recommender System Using Hybrid Deep Learning Based on LSTM , SDAE and Latent Factor,” International Journal of Intelligent Engineering and Systems, vol. 15, no. 2, pp. 379–393, 2022, doi: 10.22266/ijies2022.0430.35.

[20] S. Chen and M. Wu, “Attention collaborative autoencoder for explicit recommender systems,” Electronics (Switzerland), vol. 9, no. 10, pp. 1–12, 2020, doi: 10.3390/electronics9101716.

[21] B. Zhang, H. Zhang, X. Sun, G. Feng, and C. He, “Integrating an attention mechanism and convolution collaborative filtering for document context-aware rating prediction,” IEEE Access, vol. 7, pp. 3826–3835, 2019, doi: 10.1109/ACCESS.2018.2887100.

[22] R. Salakhutdinov and A. Mnih, “Probabilistic Matrix Factorization.,” Proc. Advances in Neural Information Processing Systems 20 (NIPS 07), pp. 1257–1264, 2007, doi: 10.1145/1390156.1390267.

[23] C. Wang and D. M. Blei, “Collaborative Topic Modeling for Recommending Scientific Articles,” Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD ’11, p. 448, 2011, doi: 10.1145/2020408.2020480.

[24] J. Wei, J. He, K. Chen, Y. Zhou, and Z. Tang, “Collaborative Filtering and Deep Learning Based Hybrid Recommendation for Cold Start Problem,” 2016 IEEE 14th Intl Conf on Dependable, Autonomic and Secure Computing, 14th Intl Conf on Pervasive Intelligence and Computing, 2nd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress(DASC/PiCom/DataCom/CyberSci Tech), pp. 874–877, 2016, doi: 10.1109/DASC-PICom-DataCom-CyberSciTec.2016.149.

[25] Hanafi, N. Suryana, and A. S. B. H. Basari, “Convolutional-NN and word embedding for making an effective product recommendation based on enhanced contextual understanding of a product review,” International Journal on Advanced Science, Engineering and Information Technology, vol. 9, no. 3, 2019, doi: 10.18517/ijaseit.9.3.8843.

[26] Hanafi, N. Suryana, and A. S. H. Basari, “Involve Convolutional-NN to Generate Item Latent Factor Consider Product Genre to Increase Robustness in Product Sparse Data for E-commerce Recommendation,” in Journal of Physics: Conference Series, 2019, vol. 1201, no. 1. doi: 10.1088/1742-6596/1201/1/012004.

[27] Hanafi, N. Suryana, and A. S. H. Basari, “Dynamic convolutional neural network for eliminating item sparse data on recommender system,” International Journal of Advances in Intelligent Informatics, vol. 4, no. 3, 2018, doi: 10.26555/ijain.v4i3.291.

[28] Hanafi, A. Pranolo, and Y. Mao, “Cae-covidx: Automatic covid-19 disease detection based on x-ray images using enhanced deep convolutional and autoencoder,” International Journal of Advances in Intelligent Informatics, vol. 7, no. 1, pp. 49–62, 2021, doi: 10.26555/ijain.v7i1.577.

[29] Hanafi, N. Suryana, and A. S. H. Basari, “Involve Convolutional-NN to Generate Item Latent Factor Consider Product Genre to Increase Robustness in Product Sparse Data for E-commerce Recommendation,” Journal of Physics: Conference Series, vol. 1201, no. 1, 2019, doi: 10.1088/1742-6596/1201/1/012004.

[30] Hanafi, N. Suryana, and A. S. B. H. Basari, “Convolutional-NN and word embedding for making an effective product recommendation based on enhanced contextual understanding of a product review,” International Journal on Advanced Science, Engineering and Information Technology, vol. 9, no. 3, pp. 1063–1070, 2019, doi: 10.18517/ijaseit.9.3.8843.

[31] Hanafi, N. Suryana, and A. S. B. H. BASARI, "Recommender System Based Tensor Candecomp Parafact Algorithm-ALS to Handle Sparse Data In Food Commerce Information Services," IJSSST, pp. 1–9, 2019, doi: 10.5013/IJSSST.a.19.06.60.

[32] Hanafi, N. Suryana, and A. Samad, "Dynamic convolutional neural network for eliminating item sparse data on recommender system," IJAIN, vol. 4, no. 3, pp. 226–237, 2018.

[33] P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, and P.-A. Manzagol, "Stacked Denoising Autoencoders: Learning Useful Representations in a Deep Network with a Local Denoising Criterion Pierre-Antoine Manzagol," Journal of Machine Learning Research, vol. 11, pp. 3371–3408, 2010, doi: 10.1111/1467-8535.00290.

[34] J. Chorowski, D. Bahdanau, D. Serdyuk, K. Cho, and Y. Bengio, "Attention-based models for speech recognition," Advances in Neural Information Processing Systems, vol. 2015-Janua, pp. 577–585, 2015.

Enhance Rating Prediction for E-commerce Recommender System using Hybridization SDAE, Attention Mechanism and Matrix Factorization

ORIGINALITY REPORT

12%	9%	6%	4%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Amity University Student Paper	3%
2	inass.org Internet Source	2%
3	www.hindawi.com Internet Source	2%
4	Hanafi, Burhanuddin Mohd Aboobaider. "Word Sequential Using Deep LSTM and Matrix Factorization to Handle Rating Sparse Data for E-Commerce Recommender System", Computational Intelligence and Neuroscience, 2021 Publication	1%
5	proceedings.mlr.press Internet Source	1%
6	Hanafi, N Suryana, ASH Basari. "Generate Contextual Insight of Product Review Using	<1%

Deep LSTM and Word Embedding", Journal of Physics: Conference Series, 2020
Publication

7	Submitted to B.S. Abdur Rahman University Student Paper	<1 %
8	www.researchgate.net Internet Source	<1 %
9	www.sciencegate.app Internet Source	<1 %
10	Lecture Notes in Computer Science, 2015. Publication	<1 %
11	edas.info Internet Source	<1 %
12	Hanafi, N Suryana, A S H Basari. "Involve Convolutional-NN to Generate Item Latent Factor Consider Product Genre to Increase Robustness in Product Sparse Data for E-commerce Recommendation", Journal of Physics: Conference Series, 2019 Publication	<1 %
13	Sidahmed Benabderrahmane, Nedra Mellouli, Myriam Lamolle. "On the predictive analysis of behavioral massive job data using embedded clustering and deep recurrent neural networks", Knowledge-Based Systems, 2018 Publication	<1 %

14	library.ndsu.edu Internet Source	<1%
15	Xiangquan Zhang, Zhili Ma, Anmin Wang, Haifeng Mi, Junjun Hang. "LstFcFedLear: A LSTM-FC with Vertical Federated Learning Network for Fault Prediction", Wireless Communications and Mobile Computing, 2021 Publication	<1%

Exclude quotes	Off	Exclude matches	Off
Exclude bibliography	On		

Enhance Rating Prediction for E-commerce Recommender System using Hybridization SDAE, Attention Mechanism and Matrix Factorization

GRADEMARK REPORT

FINAL GRADE

/0

GENERAL COMMENTS

Instructor

PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11