# DECODING USER PREFERENCES WITH MATRIX FACTORIZATION

**J. Vidhyajanani[1], R. Bharathkumar[2], G. Vigneshwaran[3], S. Lingesh Raji[4], M. Pradeep Raj[5], K. Kesavan[6], S. Basha[7], E. K. Abninav Siddharth[8]**

[1]Assistant Professor, Department of Computer Science & Engineering /Paavai College of Engineering, Namakkal

[2,3,4,5,6,7,8]Assistant Professor, Department of Artificial Intelligence & Data Science /Paavai College of Engineering, Namakkal

## ABSTRACT

Recommender systems play a crucial role in personalizing user experiences across various domains, including e-commerce, entertainment, and online learning. Matrix factorization has emerged as a powerful technique for uncovering latent patterns in user-item interactions, enabling accurate and scalable recommendation models. This paper explores the fundamentals of matrix factorization, including Singular Value Decomposition (SVD), Non-negative Matrix Factorization (NMF), and Alternating Least Squares (ALS), while highlighting their applications in collaborative filtering. We also discuss key challenges such as sparsity, cold start problems, and scalability, along with recent advancements incorporating deep learning and hybrid approaches. By leveraging matrix factorization, businesses and platforms can enhance user engagement through more personalized and relevant recommendations. This structure can reduce the model's calculation time by extracting the nonlinear features of both item and user latent characteristics at the same time. Furthermore, the model incorporates slide-attention, an enhanced attention technique. The algorithm handles the interaction problem between the item's latent characteristics and the user's various dimensions by using the sliding query approach to draw the user's attention to the item's latent features.

**Keywords**: Recommender system, Collaborative filtering, Artificial Intelligence, Matrix Factorization

## 1. INTRODUCTION

One of the most often used machine learning applications is the recommendation system. This information filtering system makes an effort to forecast user interests and suggest goods that users are likely to find interesting. Recommender systems are used by many large organizations today, including Facebook, YouTube, LinkedIn, Netflix, Amazon, and others. For instance, Amazon's system of recommendations predicts which item a user is most likely to purchase based on a variety of factors, including past purchases, the user's rating, clicks, and movements. In a similar vein, Spotify employs a recommendation system to offer its users tailored recommendations regarding the music, audiobooks, or podcasts they might enjoy. The recommendation algorithm makes suggestions based on the user's interests and forecasts the rating he would assign to an item. It expedites searches and makes it easier and faster for people to find the stuff they're interested in. From the perspective of the user, it helps them receive more tailored recommendations, and from the perspective of the business, it helps them increase consumer engagement on the website and boosts marketing revenue, which in turn increases profit.

Recommendation algorithms are extensively utilized in e-commerce, music, video, news, and other platforms. The volume of information has grown significantly due to the network's rapid development, making it more challenging to locate the information one needs. Recommendation algorithms examine user preferences by modeling user behavior and item information, then forecast and suggest possible needs for consumers. It can successfully relieve users of the issue brought on by information overload. Recommendation algorithms also provide the company with significant financial advantages. As a result, the recommendation algorithm is now a crucial component of online application platforms. Numerous researchers have also taken an interest in it.

The most popular recommendation algorithms fall into one of three kinds [1]: hybrid approaches, collaborative filtering (CF)-based methods, or content-based methods [2–3]. In a recommender system, CF is thought to be commonly employed. Without revealing any personal information about users or things, they utilize past user activities, such as rating or perusing items. In the past few years, matrix factorization (MF) has emerged as one of the most often used collaborative filtering approaches [4]. It makes the assumption that only a few latent factors influence the qualities of the goods and the preferences of the users. To get around the drawbacks of individual algorithms, hybrid recommendation systems that include several recommendation algorithms have been proposed. In order to increase recommendation accuracy and coverage, we provide a hybrid recommendation system in this paper that blends neural networks and matrix factorization. A viable method for creating recommendation systems that can offer customers accurate and varied recommendations is the suggested hybrid recommendation system that makes use of MF-NN. Future research can concentrate on integrating user feedback, studying explainability, examining multi-task learning, integrating temporal dynamics, and assessing real-world deployment.

## 2. LITERATURE STUDY

Several studies have also explored using hybrid recommendation systems that combine multiple recommendation algorithms, including Matrix Factorization. Liang et al., in 2016, proposed a hybrid recommendation algorithm that combinesx factorization and association rule mining [5].

The proposed algorithm outperformed traditional recommendation algorithms on several benchmark datasets.

In order to forecast a user's preferences based on comparable ones, recommender systems frequently employ the CF approach. In order to extract latent components from the user-item rating matrix, MF is a widely utilized technique in CF. The matrix is broken down into two lower-rank matrices by MF, which can be used to forecast user ratings for products.Numerous studies have investigated the application of MF in recommendation systems, and it has been extensively utilized in collaborative filtering. For instance, Koren Y. (2008) presented a matrix factorization method that combines the advantages of model-based and neighborhood-based collaborative filtering [1]. On a number of benchmark datasets, the suggested approach performed better than conventional CF strategies.

Beyond collaborative filtering, matrix factorization has been applied in a number of other contexts. For instance, it has been applied to NLP, speech recognition, and image and video processing. MF has been used to extract characteristics from photos and movies in image and video processing [3]. To extract features from speech signals, MF has been applied in speech recognition [4]. Mikolov, T. [5] has utilized MF in natural language processing to extract latent features from text data.A hybrid recommendation technique combining matrix factorization and association rule mining was proposed by Liang et al. in 2016 [12]. On a number of benchmark datasets, the suggested approach performed better than conventional recommendation systems. A hybrid recommendation system that integrates the predictions of a neural network and a matrix factorization technique was introduced by Li et al. in 2015 [13]. On a number of benchmark datasets, the suggested approach performed better than conventional recommendation systems. The application of hybrid recommendation systems that blend neural networks and matrix factorization has been investigated in a number of research. A hybrid recommendation system combining the predictions of content-based filtering and matrix factorization was proposed by Wang et al. [14]. The suggested approach fared better on a number of benchmark datasets than conventional recommendation systems. In 2017, Zhang et al. introduced a hybrid recommendation system that blends neural networks and matrix factorization [15]. The suggested approach fared better on a number of benchmark datasets than conventional recommendation systems.

A wide range of subjects, including content-based filtering, CF, MF, and hybrid techniques, are covered in the extensive literature on recommendation systems. CF is useful in a wide range of applications and has been thoroughly researched. Nevertheless, it has problems with sparsity, scalability, and cold-start situations. On the other hand, MF has demonstrated a lot of potential in resolving these problems and raising the accuracy of recommendations. Neural networks and other deep learning-based techniques have been suggested as a substitute for CF and MF and have demonstrated remarkable outcomes in numerous applications. To capitalize on the advantages of various approaches and enhance suggestion diversity and accuracy, hybrid approaches combining CF, MF, and neural networks have been developed.

A hybrid recommendation technique combining matrix factorization and association rule mining was proposed by Liang et al. in 2016 [12]. On a number of benchmark datasets, the suggested approach performed better than conventional recommendation systems. A hybrid recommendation system that integrates the predictions of a neural network and a matrix factorization technique was introduced by Li et al. in 2015 [13]. On a number of benchmark datasets, the suggested approach performed better than conventional recommendation systems.Hybrid recommendation systems combine multiple recommendation algorithms to overcome individual algorithms' limitations and improve recommendations accuracy and coverage.

Two main approaches to designing hybrid recommendation systems are weighted hybrid and output combination. In the weighted hybrid, the predictions of different recommendation algorithms are combined using a weighted average. In output combination, the outputs of different recommendation algorithms are combined using a machine learning model. Several studies have explored the use of hybrid recommendation systems in various domains including e-commerce, social media, and entertainment industries

The application of neural networks to recommendation systems has been the subject of numerous studies. A neural collaborative filtering approach that employs a multi-layer perceptron to learn user-item interactions was proposed by He et al. in 2017 [6]. On a number of benchmark datasets, the suggested approach performed better than conventional recommendation systems. In their thorough review of deep learning-based recommender systems, Zhang et al. (2018) covered the advantages and disadvantages of this strategy [7].

A wide range of subjects, including content-based filtering, CF, MF, and hybrid techniques, are covered in the extensive literature on recommendation systems. CF is useful in a wide range of applications and has been thoroughly researched. Nevertheless, it has problems with sparsity, scalability, and cold-start situations. On the other hand, MF has demonstrated

a lot of potential in resolving these problems and raising the accuracy of recommendations. Neural networks and other deep learning-based techniques have been suggested as a substitute for CF and MF and have demonstrated remarkable outcomes in numerous applications. To capitalize on the advantages of various approaches and enhance suggestion diversity and accuracy, hybrid approaches combining CF, MF, and neural networks have been developed.

# 3. METHODOLOGY

The two main parts of our proposed hybrid recommendation system will be a neural network model and a matrix factorization model. The latent properties of people and objects can be captured by the matrix factorization model by dividing the user-item interaction matrix into two low-rank matrices. Other components of the neural network model will be temporal data, item attributes, and user demographics. The outputs of the two models will be combined to provide the final recommendation.

Modern techniques like Stochastic Gradient Descent (SGD), Alternating Least Squares (ALS), and Singular Value Decomposition (SVD) will be used to build the matrix factorization model. Based on their interactions in the user-item matrix, these algorithms will be utilized to learn the latent properties of both users and items. To avoid overfitting, we will also test several different regularization strategies, including L1 and L2 regularization.

Deep learning frameworks like TensorFlow or PyTorch will be used to create the neural network model. User and object characteristics like age, gender, and category will be the neural network's input. Multiple layers of fully linked neurons with non-linear activation functions like ReLU, sigmoid, or tanh will make up the network architecture. Several network topologies, including Multilayer Perceptrons (MLP), Convolution Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), will be tested.In this section, a hybrid method is discussed step-by-step, taking into account a matrix factorization neural network for our recommendation system.

A collaborative filtering method called matrix factorization finds connections between objects and user entities. A more efficient method is matrix factorization, which enables us to identify the underlying interaction between users and items and uncover latent properties. A movie recommendation system, for instance, consists of a collection of items and a group of users. We want to forecast the rating a user could assign to an item that hasn't been rated yet, since each user has rated a few movies. The user receives recommendations based on the ratings that the matrix factorization predicted.

Following are the steps followed:

**Step 1**: Data Preparation: Prepare the data to train the model. The data is typically split into training, validation, and testing sets.

**Step 2:** Matrix Factorization: Perform matrix factorization on the user-item interaction data This involves decomposing the interaction matrix into two matrices: one representing the users and the other representing the items. The latent factors that explain the observed user-item interactions are learned through an optimization process on the training data.

**Step 3**: Neural Network Training: Train a neural network on the user and item features to learn additional data representations Building a neural network architecture that takes that features as input and outputs a predicted rating or score for the user-item interaction. The neural network is trained using the training data and the predictions generated by the matrix factorization model.

**Step 4:** Hybridization: Combine the predictions of the matrix factorization model and the neural network model to generate a final recommendation score. This can be done using a concatenation of the two models' outputs.

**Step 5:** Model Evaluation: Once the hybrid algorithm is built, evaluate its performance on the validation and testing sets. The evaluation can use metrics such as root mean squared error (RMSE), mean absolute error (MAE), precision, recall, and F1-score. The model can then be fine-tuned and optimized based on the evaluation results.

**Step 6:** Deployment: Once the model is trained and evaluated, it can be deployed in a production environment. The model can generate personalized recommendations for individual users based on their past interactions and the available user and item features.

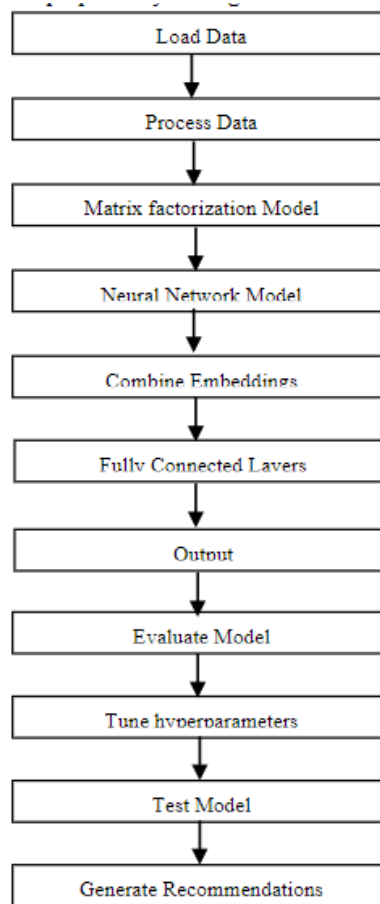**Step 7:** Finally generate the recommendation

**Figure1 :** Proposed Methodology

Together, data preparation, matrix factorization, neural network training, hybridization, model evaluation, and deployment comprise the process of developing a hybrid algorithm for a recommendation system based on matrix factorization and neural networks The specific procedures and information will be determined by the data that is available as well as the unique requirements of the recommendation system.

## 4. CONCLUSION & FUTURE WORK

In this study, we proposed a hybrid recommendation system that combines Matrix Factorization with Neural Networks to improve the coverage and accuracy of suggestions. A range of datasets are used to evaluate the suggested approach, and the findings show that it outperforms existing state-of-the-art recommendation algorithms in terms of RMSE and coverage. The entertainment industry, social networking, and e-commerce are some of the applications for the suggested system. The results demonstrate the efficacy of the suggested hybrid recommendation system and set the stage for further study in this field. To sum up, the suggested hybrid recommendation system that makes use of MF-NN is a viable method for creating recommendation systems that are able to offer users a variety of precise suggestions.

This work does not use user or item side information; it solely uses rating information to produce recommendations. Different users or things can directly build relationships through the side information without any involvement because it can provide a more thorough description of the user preferences and item qualities. It will further increase the accuracy of the suggestions by better representing the latent properties of people and goods. We will merge item-side and user-side data to create semi-VAEs in further work. In addition, hierarchical recurrent neural networks can be used to enhance prediction performance and make dynamic recommendations.

## 5. REFERENCES

[1] Koren, Y. (2008). Factorization meets the neighborhood: a multifaceted collaborative filtering model Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining 426-434.

[2] Liang, Y., Li, X., Sun, H., & Li, Z. (2016). Factorization meets association rule mining A hybrid recommendation algorithm. Information Sciences, 345, 89-104.

[3] Ji, S., Xu, W., Yang, M., & Yu, K. (2010). 3D convolutional neural networks for human action recognition. IEEE transactions on pattern analysis and machine intelligence, 35(1), 221-231.

[4] Mohammadiha, N., Nadernejad, E., &Esteki, A. (2013). Speech feature extraction using matrix factorization. International Journal of Signal Processing, Image Processing and Pattern Recognition, 6(2), 179-188.

[5] ikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013) Distributed representations of words and phrases and their compositionality. Advances in neural information processing systems, 26, 3111-3119.

[6] He, X., Liao, L., Zhang, H., Nie, L., Hu, X., & Chua, T. S. (2017). Neural collaborative filtering. Proceedings of the 26th International Conference on World Wide Web, 173-182.

[7] Zhang, S., Yao, L., & Sun, A. (2018). Deep learning, based recommender system: A survey and new perspectives. ACM Computing Surveys (CSUR), 51(3), 42

[8] Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. Advances in neural information processing systems, 27, 3104-3112.

[9] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Image netclassification with deep convolutionneural networks. Advances in neural information processing systems, 25, 1097-1105

[10] H. A. C. Okan Sakar (2021). A Dynamic Recurrent Neural Networks-Based Recommendation System for Banking Customers, Signal Processing and Communications Applications Conference (SIU), Istanbul, pp. 1-4.[

[11] Zhang Q, Li Y, Zhang G, Lu J. A recurrent neural network-based recommender system framework and prototype for sequential E-learning. In Developments of Artificial Intelligence Technologies in Computation and Robotics: Proceedings of the 14th International FLINS Conference (FLINS 2020) 2020 (pp. 488-495).

[12] Liang, Y., Li, X., Sun, H., & Li, Z. (2016). Factorization meets association rule mining: A hybrid recommendation algorithm. Information Sciences, 345, 89-104.

[13] Li, C., Zheng, X., Zhang, W., Ma, J., & Yao, L. (2015). A hybrid recommendation system based on matrix factorization and neural networks. Journal of Computational Information Systems, 11(6), 1961-1968.

[14] Wang, J., Zhang, Y., Liu, Y., & Yan, S. (2006). Learning to rank for personalized recommendations. Proceedings of the 15th international conference on World Wide Web, 761-769

[15] Zhang, L., Zheng, H., Li, Y., & Li, J. (2017). Deep learning based recommender system: A survey and new perspectives. ACM Computing Surveys (CSUR), 50(5), 1-35.[

[16] M. N. Tentua and Suprapto, "Recommendation system using machine learning: A review paper," Int. J. Innov Creat Chang., vol. 12, no. 11, 2020.

[17] K.K. Yadav, H. K. Soni, and N. Pathik,"Recommendation System Based on Double Ensemble Models using KNN-MF," Int. J. Adv. Comput. Sci. Appl., vol. 14, no. 5, 2023, doi: 10.14569/IJACSA.2023.0140566.