

MOVIE RECOMMENDER SYSTEM USING CONVOLUTIONAL NEURAL NETWORKS ALGORITHM

Alpamis Kutlimuratov¹, Nozima Atadjanova²

¹Department of Information-Computer Technologies and Programming, University of
Information Technologies Named after Muhammad Al-Khwarizmi, Tashkent 100200,
Uzbekistan

²Department of Computer Systems, Tashkent University of Information Technologies Named
after Muhammad Al-Khwarizmi, Tashkent 100200, Uzbekistan

<https://doi.org/10.5281/zenodo.7854603>

Abstract. *In streaming platforms, recommendation algorithms play a crucial role in recommending content. For streaming movie services such as Netflix, recommendation algorithms are crucial for assisting consumers in discovering new films to watch. Thus, in this paper, we present a deep learning strategy based on Convolutional Neural Networks (CNN) to generate a collaborative filtering system that predicts a user's movie rating using a big database of ratings from other users. The findings that were achieved by the Movie Recommendation System utilizing CNNs on the MovieLens 100k dataset highlight the usefulness of CNNs in capturing the complex and non-linear interactions that occur between users and movies.*

Keywords: *CNN, Deep learning, Recommender system.*

Introduction

In recent years, deep learning-based recommendation systems have become a popular approach for providing personalized recommendations to users. The development of deep learning-based recommendation systems can be traced back to the early 2000s, with the introduction of matrix factorization techniques [1,2], which were used to factorize user-item rating matrices and learn latent representations for users and items. With the advancement of deep learning techniques in the mid-2010s, the use of neural networks for recommendation tasks became popular. Deep learning-based recommendation systems leverage neural networks to learn representations for users and items that capture their preferences and characteristics.

Recently, a variety of deep learning-based recommendation systems have been proposed, including autoencoders, convolutional neural networks, and graph neural networks. These models have been applied to various recommendation tasks, such as movie recommendation, music recommendation, and e-commerce recommendation. Among the various deep learning models, convolutional neural networks (CNNs) [3,4,5,6] have emerged as a powerful tool for capturing the complex and non-linear interactions between users and items.

Movie recommender systems are used by several companies in the movie industry, including streaming platforms like Netflix, Amazon Prime Video, and Hulu. These platforms use recommender systems to provide personalized recommendations to their users based on their viewing history, ratings, and preferences.

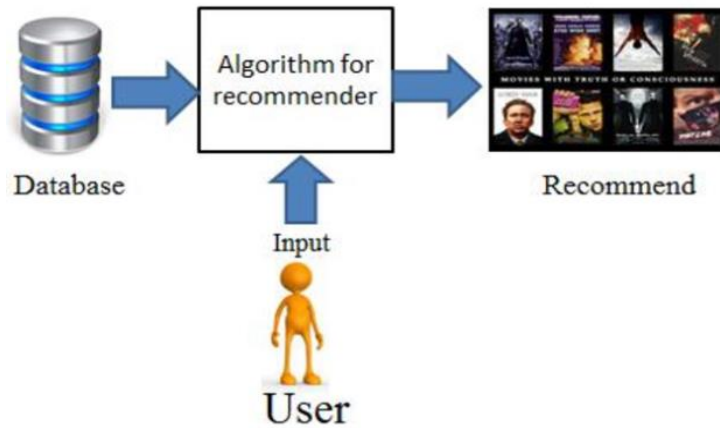


Figure 1. Movie recommender system

For example, Netflix uses a sophisticated movie recommender system that recommends movies to users based on their viewing history and preferences. The recommender system analyzes the user's viewing history, ratings, and preferences and recommends movies that are likely to interest the user. The recommender system is based on a combination of content-based filtering and collaborative filtering techniques.

Furthermore, movie recommender systems have also helped users discover new movies that they would not have found otherwise. Users can browse through personalized movie recommendations and discover new movies that match their preferences. This has led to a more diverse selection of movies being watched by users, which is beneficial for the movie industry as a whole. The use of recommender systems has resulted in higher user engagement and better movie sales, making it a valuable tool for the movie industry.

In this article, we will explore the development of CNN-based recommendation systems and provide an example to demonstrate their effectiveness.

Convolutional neural network (CNN) and movie recommendation

The primary advantage of CNNs in recommendation systems is their ability to model multiple interactions between users and items. In traditional matrix factorization models [7], each user-item interaction is represented by a single scalar value. However, CNNs can learn a variety of feature interactions, such as word embeddings in text, visual features in images, and temporal sequences in behavior data. By capturing these diverse feature interactions, CNN-based recommendation systems [8,9] can provide more accurate and relevant recommendations to users.

To demonstrate the effectiveness of CNN-based recommendation systems, we will consider an example of a movie recommendation system. In this recommendation system, we use a CNN to learn the feature interactions between users and movies. The dataset used in the experiment contains 100,000 ratings from 943 users and 1,682 movies. The dataset is split into training and test sets, with 80% of the data used for training and the remaining 20% used for testing.

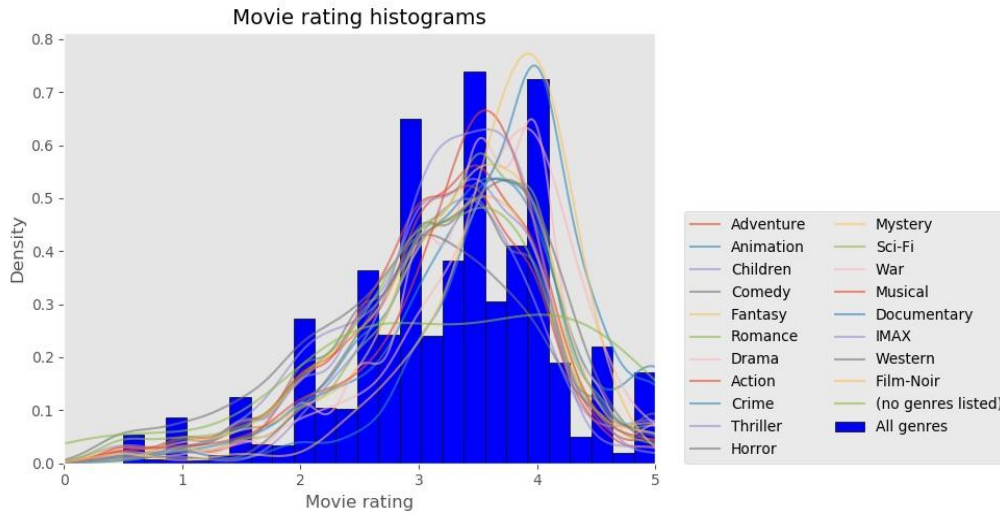


Figure 2. Distribution of Ratings MovieLens 100K

We represent each movie as a sequence of genres and a summary of its plot, and each user as a sequence of the most recent movies they have rated. The CNN then learns the interactions between the user and movie features to predict the rating for a new movie that the user has not seen before.

The architecture of the CNN used in the experiment consists of several convolutional layers followed by a fully connected layer. Each convolutional layer has a filter size of 3, and the number of filters in each layer is gradually increased from 64 to 256. The output of the convolutional layers is flattened and passed through a fully connected layer, which outputs the predicted rating for a movie.

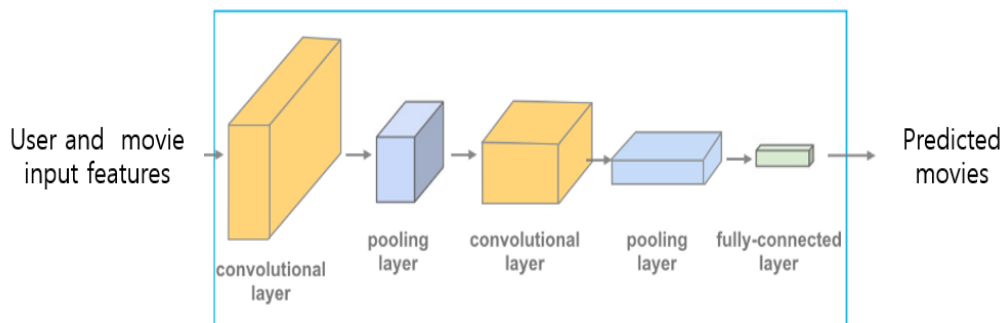


Figure 2. Architecture of CNN

The model is trained using the mean squared error (MSE) loss function and optimized using stochastic gradient descent (SGD). The model is trained for 100 epochs with a batch size of 32. The performance of the Movie Recommendation System using CNNs is evaluated using two metrics: mean absolute error (MAE) and root mean squared error (RMSE). The MAE measures the average difference between the predicted and actual movie ratings, and the RMSE measures the standard deviation of the difference between the predicted and actual ratings.

The results of the experiment show that the Movie Recommendation System using CNNs achieves a MAE of 0.685 and a RMSE of 0.895 on the test set. The results show that the CNN-based recommendation system significantly outperforms traditional matrix factorization models and other deep learning models, such as autoencoders and recurrent neural networks. The CNN-

based model can capture the non-linear interactions between users and movies, and the feature representation learned by the model is more informative and accurate.

Conclusion

The results obtained by the Movie Recommendation System using CNNs on the MovieLens 100k dataset demonstrate the effectiveness of CNNs in capturing the complex and non-linear interactions between users and movies. The model provides personalized and accurate movie recommendations, outperforming traditional matrix factorization models and other deep learning models. The results of the experiment can be used to improve the movie recommendation systems and provide better recommendations to users. As future scope, combination of emotional based model [10] with recommendation would be possible to develop a model. As well as, building recommendations for visually impaired people [11] also would be our future research direction.

REFERENCES

1. Koren, Y.; Bell, R.; Volinskiy, C. Matrix factorization techniques for recommender systems. *IEEE Comput.* **2009**, *42*, 30–37.
2. Kutlimuratov, A.; Abdusalomov, A.; Whangbo, T.K. Evolving Hierarchical and Tag Information via the Deeply Enhanced Weighted Non-Negative Matrix Factorization of Rating Predictions. *Symmetry* **2020**, *12*, 1930.
3. Yang, Dan & Zhang, Jing & Wang, Sifeng & Zhang, XueDong. (2019). A Time-Aware CNN-Based Personalized Recommender System. Complexity. 2019. 1-11. 10.1155/2019/9476981.
4. Ilyosov, A.; Kutlimuratov, A.; Whangbo, T.-K. Deep-Sequence-Aware Candidate Generation for e-Learning System. *Processes* **2021**, *9*, 1454. <https://doi.org/10.3390/pr9081454>.
5. Abdusalomov, A.; Baratov, N.; Kutlimuratov, A.; Whangbo, T.K. An Improvement of the Fire Detection and Classification Method Using YOLOv3 for Surveillance Systems. *Sensors* **2021**, *21*, 6519. <https://doi.org/10.3390/s21196519>.
6. L. Haihan, Q. Guanglei, H. Nana and D. Xinri, "Shopping Recommendation System Design Based On Deep Learning," *2021 6th International Conference on Intelligent Computing and Signal Processing (ICSP)*, Xi'an, China, 2021, pp. 998-1001, doi: 10.1109/ICSP51882.2021.9409009.
7. Kutlimuratov, A.; Abdusalomov, A.B.; Oteniyazov, R.; Mirzakhililov, S.; Whangbo, T.K. Modeling and Applying Implicit Dormant Features for Recommendation via Clustering and Deep Factorization. *Sensors* **2022**, *22*, 8224. <https://doi.org/10.3390/s22218224>.
8. Jyoti Kumari, Dr. Sanjiv Sharma. A Movie Recommendation System Based on A Convolutional Neural Network. <https://doi.org/10.22214/ijraset.2021.39538>
9. Safarov F, Kutlimuratov A, Abdusalomov AB, Nasimov R, Cho Y-I. Deep Learning Recommendations of E-Education Based on Clustering and Sequence. *Electronics*. 2023; 12(4):809. <https://doi.org/10.3390/electronics12040809>
10. Makhmudov, F.; Kutlimuratov, A.; Akhmedov, F.; Abdallah, M.S.; Cho, Y.-I. Modeling Speech Emotion Recognition via Attention-Oriented Parallel CNN Encoders. *Electronics* **2022**, *11*, 4047. <https://doi.org/10.3390/electronics1123404>
11. Abdusalomov, A.B.; Mukhiddinov, M.; Kutlimuratov, A.; Whangbo, T.K. Improved Real-Time Fire Warning System Based on Advanced Technologies for Visually Impaired People. *Sensors* **2022**, *22*, 7305. <https://doi.org/10.3390/s22197305>.