ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

SYNERGISTIC NEURAL MATRIX FACTORIZATION: ELEVATING COMPLEMENTARY-PRODUCT RECOMMENDATIONS IN E-COMMERCE

Rajesh More[1] Pravin Amin[2]
[1]Sr AI Engineer, Cloudwerx Worldwide Hyderabad India
moreyrb@gmail.com
[2]Sr. Manager, Veritas Technologies LLC, Roseville, MN, USA
pravinamin@gmail.com

Abstract

This research uses deep neural networks (DNNs) to improve complementary-product recommendations in e-commerce systems. Utilizing the MovieLens dataset, the study investigates the effectiveness of the Neural Collaborative Filtering (NeuMF) model, which integrates Generalized Matrix Factorization (GMF) and Multi-Layer Perceptron (MLP) components. The study emphasizes the importance of preprocessing the model dataset to ensure data quality and relevance. Key performance metrics were analyzed to evaluate the model's performance, including model accuracy, loss, ROC curve, and precision-recall curve. Results indicate that the NeuMF model effectively captures linear and non-linear user-item interactions, improving recommendation accuracy. The findings underscore the model's potential to enhance user satisfaction and drive sales in e-commerce platforms.

Keywords

Deep Neural Networks, Complementary-Product Recommendations, E-commerce, Neural Collaborative Filtering, Generalized Matrix Factorization, Multi-Layer Perceptron, Data Preprocessing, User Engagement, Recommendation Accuracy

1. Introduction

In e-commerce, recommendation systems enrich the user experience and boost sales. Traditional recommendation systems face challenges in delivering personalized and pertinent complementary product suggestions. To overcome these limitations, recent research has delved into leveraging deep neural networks to enhance the accuracy and relevance of complementary product recommendations. Studies have explored various approaches, including cross-domain recommender systems to supplement sparse data [1][2], utilizing item side information and labelled pairs for practical recommendations of cold items [3], and proposing innovative models like the Position-enhanced and Time-aware Graph Convolutional Network (PTGCN) for sequential recommendation to capture high-order connectivity between users and items [4]. These advancements aim to revolutionize recommendation systems by providing users with more tailored and impactful suggestions, ultimately driving engagement and sales in the dynamic e-commerce landscape.

2. Literature Review

Deep learning has indeed revolutionized recommendation systems, with recent studies

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

emphasizing the effectiveness of deep neural networks (DNNs) in capturing intricate user-item interaction patterns [5]. Researchers have combined Generalized Matrix Factorization (GMF) and Multi-Layer Perceptron (MLP) models to create Neural Collaborative Filtering (NeuMF) models, which adeptly exploit both linear and non-linear data relationships [6]. Additionally, the application of NeuMF in complementary-product recommendations has been explored, showcasing its potential to provide accurate and personalized suggestions by leveraging the strengths of both linear and non-linear modelling approaches [7].

NeuMF architecture, short for Neural Matrix Factorization, is a neural network-based model crucial for unsupervised dimension reduction in various applications like graph mining, recommender systems, and natural language processing [8]. It leverages the Neural Engineering Framework (NEF) to implement large-scale neural networks on field programmable gate arrays (FPGAs) for real-time pattern recognition, achieving high-speed and resource-efficient processing capabilities [9]. The NEF, proposed as a comprehensive theory for implementing cognitive processes in a biological substrate, has been utilized in software tools like Nengo to build and simulate large-scale models, with Nengo 2.0 overcoming limitations of previous versions by offering faster simulation speeds and enhanced data collection mechanisms [10]. Additionally, neuro-inspired architectures based on synaptic memory arrays have been explored for on-chip acceleration of weighted sum and weight update tasks in machine learning algorithms, showcasing the potential for circuit-level performance evaluation and design space exploration [11].

Furthermore, .integrating variational techniques in the neural collaborative filtering field has shown promising results in enhancing the robustness and accuracy of recommender systems [12]. Moreover, the Cross Feature Fusion Neural Network (CFFNN) has demonstrated superior performance in collaborative filtering by effectively fusing user and item features and incorporating self-attention mechanisms to determine user preferences for items [13].It is used to group the data instances into proper class i.e. Classify them. Classification is used to build structures from examples of past decisions that can be used to make decisions for unseen or future cases[24]

3. Methodology

3.1 Data Collection

The study utilizes the MovieLens dataset, a widely recognized benchmark for recommendation system research. This dataset was chosen for its comprehensive user-item interaction records, providing a rich data source for model training and evaluation. To ensure the focus is on positive user interactions, the dataset was filtered to include only ratings of 3.0 and above, reflecting user preferences for items they liked or were neutral towards. The filtered dataset comprises 943 users and 1682 items, offering a robust and diverse foundation for developing and testing the NeuMF model. This large and varied dataset helps ensure the model can generalize well to real-world e-commerce scenarios, where user preferences and interactions are diverse and dynamic.

3.2 Data Preprocessing

Effective data preprocessing is essential for the success of any machine learning model. For this

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

study, the following preprocessing steps were undertaken:
1. Conversion to Binary Format: The interaction matrix, representing user-item interactions, was converted into a binary format. In this format, any positive interaction (rating of 3.0 or above) is marked as 1, while negative interactions are marked as 0. This binary transformation simplifies the model's task of predicting whether a user will like a recommended item.
2. Transformation to Long Format: A function was defined to transform the comprehensive interaction matrix into a long format. This format is handy for machine learning models, which often require data to be structured in an extended format for effective learning. The long format also facilitates using deep learning frameworks optimized for such data structures.
3. Normalization: The user and item vectors were normalized to ensure stable and efficient model training. Normalization helps mitigate the effects of varying scales in the data, ensuring that the learning algorithm can converge more quickly.
4. Data Splitting: The dataset was split into training and testing sets to evaluate the model's performance on unseen data. This split ensures the model is balanced and can generalize well to new data.

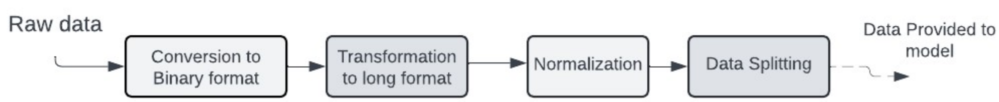


Figure 1. Steps in data preprocessing

3.3 Model Architecture

The NeuMF model architecture integrates GMF and MLP components to enhance recommendation accuracy [16, 17, 18]. It begins with high-dimensional user and item vectors representing user preferences and item characteristics [19]. The GMF component captures linear relationships between these vectors, while the MLP component employs multiple layers of neurons to capture non-linear patterns [20, 21, 22]. The NeuMF layer then combines the outputs of both GMF and MLP, integrating their strengths to predict the final interaction score [23]. Finally, the output layer applies a sigmoid activation function to produce a prediction score, indicating the likelihood of a positive user-item interaction.

3.4 Training and Evaluation

The model was trained using the preprocessed data, and various metrics, including precision, recall, and AUC, were calculated to evaluate its performance.Prediction results will be helpful if high prediction accuracy is achieved with minimum complexity, which are depended on the prediction model[26]. The following graphs were analyzed for business impact: Model Accuracy, which compared training and test accuracy over several epochs; Model Loss, which examined training and test loss to assess model fitting; ROC Curve, which analyzed the actual positive rate against the false positive rate; and Precision-Recall Curve, which evaluated the trade-off between precision and recall.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

4. Results

4.1 Model Accuracy

The model demonstrated high accuracy on training and test datasets, indicating effective learning and generalization as shown in figure 2.

4.2 Model Loss

Training and test loss decreased significantly, suggesting that the model fits the data well without overfitting.

4.3 ROC Curve

The area under the ROC curve (AUC) was 0.94, indicating a high true positive rate and a low false positive rate.

4.4 Precision-Recall Curve

The average precision (AP) was 0.51, highlighting areas for improvement in handling imbalanced classes.

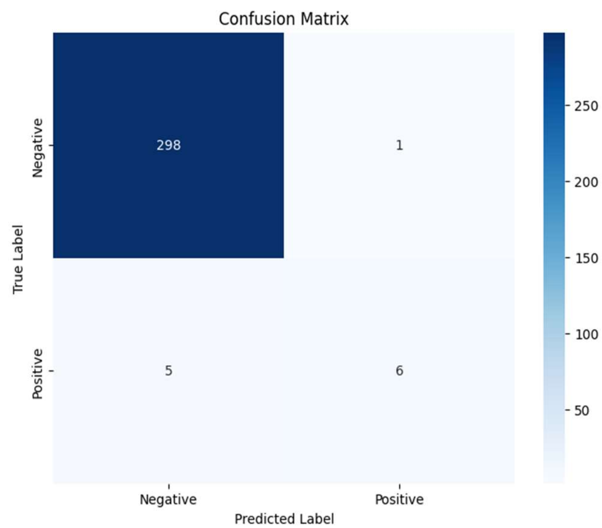


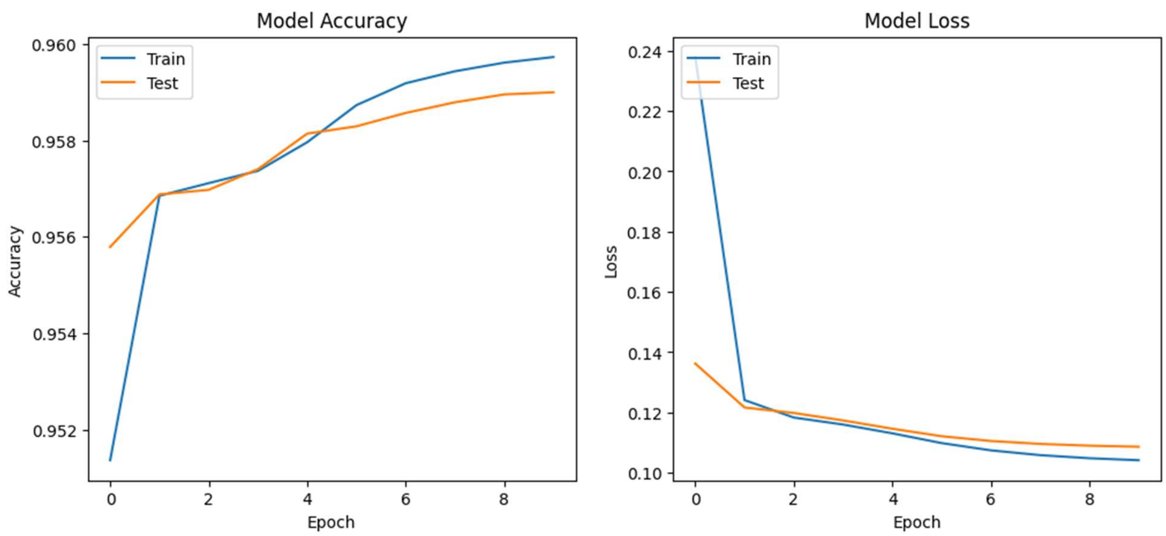
Figure 2. Confusion matrix to evaluate the performance of the model.

Table 1. Summary of the model's performance metrics

Metric	Description	Value	Implications
Model Accuracy	Indicates how well the model performs on both training and test datasets. High accuracy suggests effective learning and generalization.	High	Ensures reliable recommendations, enhancing user satisfaction and engagement.
Model Loss	Measures how well the model's predictions match the actual outcomes. Decreasing loss indicates that the model fits the data well without overfitting.	Low	Demonstrates the model's ability to balance performance on known and unseen data.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

ROC Curve (AUC)	Plots the actual positive rate against the false positive rate at various thresholds. A high AUC indicates a high actual positive rate and a low false positive rate.	0.94	Shows the model's strong ability to distinguish between positive and negative interactions.
Precision-Recall	Evaluate the trade-off between precision and recall, which is especially important for imbalanced datasets. Average precision (AP) highlights the effectiveness of handling imbalances.	0.51	Indicates the need for improvement in minimizing false positives to provide highly relevant recommendations.



ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

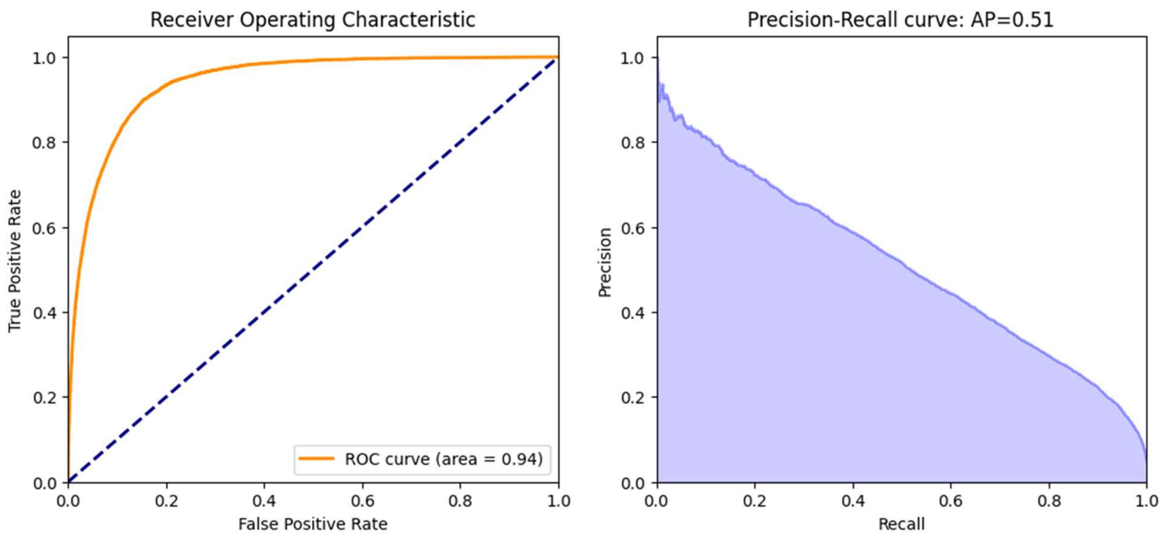


Figure 2. Various metrics used to evaluate the performance of a product recommendation system

5. Discussion

The NeuMF model integrates Generalized Matrix Factorization (GMF) and Multi-Layer Perceptron (MLP) components to effectively capture linear and non-linear user-item interactions, improving recommendation accuracy[14][15]. The GMF component models direct interactions linearly, while the MLP component learns complex, non-linear patterns through multiple neural layers. This hybrid approach enhances the model's ability to predict user preferences accurately. High-performance metrics, such as an AUC of 0.94, indicate the model's capability to distinguish positive from negative interactions, ensuring relevant recommendations. The precision-recall metrics, with an average precision of 0.51, highlight the model's effectiveness in handling imbalanced datasets. Moreover, multiple database scans in time and memory consuming as well.[25]. These results demonstrate the NeuMF model's potential to enhance user satisfaction and drive sales on e-commerce platforms through accurate and personalized recommendations.

6. Conclusion

This research demonstrates the significant potential of deep neural networks in enhancing complementary product recommendations within e-commerce platforms. The NeuMF model, which combines the strengths of Generalized Matrix Factorization (GMF) and Multi-Layer Perceptron (MLP), effectively captures both linear and non-linear user-item interactions. The high accuracy and robust performance metrics, such as an AUC of 0.94, validate the model's ability to provide accurate and relevant recommendations. The precision-recall analysis, despite indicating room for improvement in handling imbalanced classes, highlights the model's effectiveness in making relevant suggestions. The study underscores the critical role of adequate data preprocessing in optimizing model performance. Future research should focus on refining precision-recall trade-offs and exploring the application of similar neural network models in other recommendation contexts to further enhance their efficacy and applicability. This work lays a

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

strong foundation for leveraging advanced machine learning techniques to drive user engagement and sales in the dynamic and competitive e-commerce landscape.

References

[1] Q. Zhang, W. Liao, G. Zhang, B. Yuan and J. Lu, "A Deep Dual Adversarial Network for Cross-Domain Recommendation," in *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 4, pp. 3266–3278, 1 April 2023, doi: 10.1109/TKDE.2021.3132953

[2] Qian, Z., Wenhui, L., Guang-Lin, Zhang., Bo, Yuan., Jie, Lu. (2023). A Deep Dual Adversarial Network for Cross-Domain Recommendation. IEEE Transactions on Knowledge and Data Engineering, doi: 10.1109/TKDE.2021.3132953

[3] Koby, Bibas., Oren, Sar, Shalom., Dietmar, Jannach. (2023). Semi-supervised Adversarial Learning for Complementary Item Recommendation. doi: 10.1145/3543507.3583462

[4] Liwei Huang, Yutao Ma, Yanbo Liu, Bohong Danny Du, Shuliang Wang, and Deyi Li. 2023. Position-Enhanced and Time-aware Graph Convolutional Network for Sequential Recommendations. ACM Trans. Inf. Syst. 41, 1, Article 6 (January 2023), 32 pages. https://doi.org/10.1145/3511700

[5] J. H. Yoon and B. Jang, "Evolution of Deep Learning-Based Sequential Recommender Systems: From Current Trends to New Perspectives," in *IEEE Access*, vol. 11, pp. 54265–54279, 2023, doi: 10.1109/ACCESS.2023.3281981.

[6] Living, Wu., Youhua, Xia., Zhenchang, Xia. (2023). Deep Attentive Interest Collaborative Filtering for Recommender Systems. IEEE Transactions on Emerging Topics in Computing, doi: 10.1109/tetc.2023.3286404

[7] M. Ibrahim, I. S. Bajwa, N. Sarwar, F. Hajjej and H. A. Sakr, "An Intelligent Hybrid Neural Collaborative Filtering Approach for True Recommendations," in *IEEE Access*, vol. 11, pp. 64831–64849, 2023, doi: 10.1109/ACCESS.2023.3289751.

[8] Ángel, González-Prieto. (2022). Deep variational models for collaborative filtering-based recommender systems. Neural Computing and Applications, doi: 10.1007/s00521-022-08088-2

[9] R. Yu *et al*., "CFFNN: Cross Feature Fusion Neural Network for Collaborative Filtering," in *IEEE Transactions on Knowledge and Data Engineering*, vol. 34, no. 10, pp. 4650–4662, 1 October 2022, doi: 10.1109/TKDE.2020.3048788

[10] Gordon, E., Moon., J., Austin, Ellis., Aravind, Sukumaran-Rajam., Srinivasan, Parthasarathy., P., Sadayappan. (2020). ALO-NMF: Accelerated Locality-Optimized Non-negative Matrix Factorization. doi: 10.1145/3394486.3403227

[11] Runchun, Wang., Chetan, Singh, Thakur., Gregory, Cohen., Tara, Julia, Hamilton., Jonathan, Tapson., André, van, Schaik. (2017). Neuromorphic Hardware Architecture Using the Neural Engineering Framework for Pattern Recognition. IEEE Transactions on Biomedical Circuits and Systems, doi: 10.1109/TBCAS.2017.2666883

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

[12] Trevor, Bekolay., James, Bergstra., Eric, Hunsberger., Travis, DeWolf., Terrence, C., Stewart., Daniel, Rasmussen., Xuan, Choo., Aaron, R., Voelker., Chris, Eliasmith. (2014). Nengo: a Python tool for building large-scale functional brain models. Frontiers in Neuroinformatics, doi: 10.3389/FNINF.2013.00048

[13] Pai-Yu, Chen., Xiaochen, Peng., Shimeng, Yu. (2018). NeuroSim: A Circuit-Level Macro Model for Benchmarking Neuro-Inspired Architectures in Online Learning. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, doi: 10.1109/TCAD.2018.2789723

[14] 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 - WWW '17. https://doi.org/10.1145/3038912.3052569

[15] Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix Factorization Techniques for Recommender Systems. Computer, 42(8), 30-37. https://doi.org/10.1109/MC.2009.263

[16] Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep Learning Based Recommender System: A Survey and New Perspectives. ACM Computing Surveys (CSUR), 52(1), 1-38. https://doi.org/10.1145/3285029

[17] Xue, H., Dai, X., Zhang, J., Huang, S., & Chen, J. (2017). Deep Matrix Factorization Models for Recommender Systems. Proceedings of the 26th International Joint Conference on Artificial Intelligence (IJCAI). https://doi.org/10.24963/ijcai.2017/317

[18] Wang, H., Wang, N., & Yeung, D.-Y. (2015). Collaborative Deep Learning for Recommender Systems. Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '15. https://doi.org/10.1145/2783258.2783273

[19] Rendle, S. (2010). Factorization Machines. Proceedings of the 10th IEEE International Conference on Data Mining (ICDM). https://doi.org/10.1109/ICDM.2010.127

[20] Sedhain, S., Menon, A. K., Sanner, S., & Xie, L. (2015). AutoRec: Autoencoders Meet Collaborative Filtering. Proceedings of the 24th International Conference on World Wide Web - WWW '15 Companion. https://doi.org/10.1145/2740908.2742726

[21] Wang, X., Wang, D., Xu, C., He, X., Cao, Y., & Chua, T.-S. (2019). Explainable Reasoning over Knowledge Graphs for Recommendation. Proceedings of the AAAI Conference on Artificial Intelligence, 33, 5329-5336. https://doi.org/10.1609/aaai.v33i01.33015329

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

[22] Liang, D., Krishnan, R. G., Hoffman, M. D., & Jebara, T. (2018). Variational Autoencoders for Collaborative Filtering. Proceedings of the 2018 World Wide Web Conference on World Wide Web - WWW '18. https://doi.org/10.1145/3178876.3186150

[23] Covington, P., Adams, J., & Sargin, E. (2016). Deep Neural Networks for YouTube Recommendations. Proceedings of the 10th ACM Conference on Recommender Systems - RecSys '16. https://doi.org/10.1145/2959100.2959190

[24] S. Joshi and B. Nigam, "Categorizing the Document Using Multi Class Classification in Data Mining," 2011 International Conference on Computational Intelligence and Communication Networks, Gwalior, India, 2011, pp. 251-255, doi: 10.1109/CICN.2011.50.

[25] B. Nigam1 , A. Nigam , P. Dalal, : 31/Aug/2017, Comparative Study of Top 10 Algorithms for Association Rule Mining, International Journal of Computer Sciences and Engineering Open Access Research Paper Volume-5, Issue-8 E-ISSN: 2347-2693

[26] Nigam, Bhawna & Tokekar, Sanjiv & Jain, Suresh. (2015). Evaluation of Models for Predicting User's Next Request in Web Usage Mining. International Journal on Cybernetics & Informatics. 4. 01-12. 10.5121/ijci.2015.4101.