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Article

ResNetMF: Enhancing Recommendation Systems with Residual Network Matrix Factorization

Mustafa Payandenick [a,*], and Yin Chai Wang [a]

[1] Faculty Computer Science and Information Technology, Universiti Malaysia Sarawak, Kota Samarahan, Sarawak, Malaysia

* Correspondence: 19020070@siswa.unimas.my

Abstract: In this paper, we introduce ResNetMF, a groundbreaking approach that harnesses the power of residual network matrix factorization to revolutionize recommendation systems. ResNetMF integrates residual networks, renowned for their ability to capture intricate patterns and features, with matrix factorization techniques that excel in modelling user-item interactions. This fusion presents a novel solution that surpasses the limitations of traditional recommendation systems. Through comprehensive experimentation and evaluation of diverse datasets, ResNetMF demonstrates remarkable enhancements in recommendation accuracy and efficiency. By effectively capturing both linear and nonlinear relationships in user-item interactions, ResNetMF provides superior recommendation quality. The outcomes from experiments unequivocally highlight the superiority of ResNetMF over existing state-of-the-art recommendation approaches, thereby validating its innovative nature and underscoring its potential to shape the future of recommendation systems. Through the integration of the deep residual network, ResNetMF approach facilitates the training of neural networks, enabling them to explore the underlying data layers more comprehensively. Extensive experimentation and evaluation across various datasets provide compelling evidence for the superiority of ResNetMF. Moreover, the proposed method utilized natural language processing (NLP) techniques for targeted information dissemination in recommendation systems, emphasizing the importance of personalized and relevant recommendations for user satisfaction and engagement.

Keywords: recommendation systems; personalized recommendations; ResNetMF; Residual Network Matrix Factorization; deep residual network; recommendation accuracy; linear and nonlinear relationships

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1. Introduction

In recent decades, there has been an exponential growth in the amount of information available [1], mainly due to the widespread expansion of the World Wide Web [2]. This phenomenon has resulted in what is commonly referred to as information overload, where the sheer volume of information surpasses our human capacity to process and manage it effectively [3].]. As a result, scientists and researchers are continuously seeking automated techniques to deliver the correct information to the appropriate communities and targeted users. Recommendation systems have emerged as a partial solution to this challenge, leveraging Machine Learning techniques to provide personalized information based on user preferences [4]. The integration of an intelligent recommendation system that effectively disseminates information has become highly desirable.

Recommendation systems play a crucial role in facilitating personalized information filtering by suggesting relevant choices to users from vast collections [5]. These systems are designed to alleviate the overwhelming nature of extensive selection options and provide tailored recommendations based on user preferences [6].

There are three primary classifications of recommendation systems, namely content-based filtering, collaborative filtering, and hybrid filtering; each approach employs distinct methodologies to deliver personalized recommendations.

Content-based filtering focuses on user-centric approaches that leverage user profiles and item descriptions to recommend choices based on individual preferences [7]. By analyzing explicit ratings

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or implicit indicators such as user click rates, content-based filtering creates comprehensive user profiles and tailors recommendations accordingly [8]. For instance, a football enthusiast who specifically follows Real Madrid would receive recommendations primarily centred around football-related content, with a strong emphasis on Real Madrid-related items. While content-based filtering allows for item comparisons and eliminates the need for community information, it requires substantial domain knowledge and user profile data. It may lack surprise in recommendation results, limiting the exploration of diverse interests [9].

Collaborative filtering, considered one of the most widely utilized methods in building recommendation systems [10], relies on historical data of items or users to generate recommendations [11]. This approach operates under the assumption that users with similar preferences in the past are likely to have similar preferences in the future [12]. Collaborative filtering utilizes rating information to identify like-minded users and computes forecasts for the current user based on their patterns.

Memory-based collaborative filtering, a fundamental technique within this approach, uses user interaction data to make recommendations without explicit models, employing methods such as nearest-neighbour analysis [13]. In contrast, model-based collaborative filtering employs data mining and machine learning algorithms to predict user preferences by building and updating models [14].

While collaborative filtering offers advantages such as learning market segments and generating surprising results, it faces challenges with data sparsity, scalability, and the cold start problem for new items and users [15].

To overcome the limitations of individual methods, hybrid filtering techniques have emerged as a practical solution [16].]. Hybrid models combine two or more recommendation algorithms to enhance recommendation accuracy and reduce information loss [17]. By integrating approaches such as model-based collaborative filtering with item-based collaborative filtering, blending content-based and collaborative filtering algorithms, or merging model-based collaborative filtering with memory-based collaborative filtering, hybrid filtering achieves a more comprehensive and robust recommendation system. Although hybrid methods may incur higher computational costs, they have demonstrated improved accuracy in recommendations [18].

Recommendation systems serve as invaluable tools for personalized information filtering. The classifications of content-based filtering, collaborative filtering, and hybrid filtering offer distinct methodologies to address the challenges of recommendation systems [19]. Each approach has its strengths and limitations, and by leveraging hybrid filtering techniques, researchers and practitioners can achieve more accurate and comprehensive recommendations, enhancing the user experience in various domains [20].

Deep learning-based recommendation systems are gaining popularity in the recommendation task [21]. These systems use neural networks to learn complex patterns in user behaviour and item attributes to make personalized recommendations [22].

Deep learning-based recommendation systems leverage the power of neural networks to enhance the accuracy and effectiveness of recommendation algorithms. These systems have gained significant attention and popularity in recent years due to their ability to capture complex patterns and relationships in large-scale datasets [23].

Recommendation tasks have seen successful utilization of deep learning models like deep neural networks, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and advanced architectures like transformers. These models possess the capability to automatically acquire hierarchical representations of user preferences and item attributes, leading to the generation of personalized recommendations that exhibit enhanced accuracy [23,24].

Deep learning models can also effectively address challenges like the cold start problem, where there is limited or no historical data available for new users or items [25]. By leveraging transfer learning or combining content-based and collaborative filtering techniques, deep learning-based systems can make accurate recommendations even in such scenarios.

Deep learning-driven recommendation systems present exciting prospects for enhancing the accuracy, customization, and flexibility of recommendations [26]. As the field of research in this area

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continues to progress, we anticipate ongoing developments and broader implementation of deep learning techniques in recommendation systems.

Thus, this paper proposes a novel approach that is the combination of a deep learning approach and matrix factorization. A new and innovative approach has been proposed, which combines the power of Convolutional Matrix Factorization (CMF) with the superior performance of Residual Networks (ResNet). The proposed algorithm called ResnetMF (Residual Networks with Matrix Factorization) has the potential to address the limitations of CMF and offer even better results for recommendation tasks. The proposed algorithm, CMF with ResNet, can overcome the limitations of CMF and provide even better results for recommendation tasks. By using ResNet, the algorithm can learn more complex and nuanced patterns in the data, leading to more accurate recommendations. Overall, the proposed algorithm shows great promise for improving recommendation systems.

2. Related Work

In recent years, recommendation systems have garnered considerable attention across various domains, including e-commerce and tourism, due to their pivotal role in enhancing user experiences through personalized and pertinent recommendations. To tackle the challenges encountered in recommendation systems, such as sparse data, cold start problems, and accuracy enhancement, deep learning and matrix factorization techniques have emerged as robust approaches [27,28].

This article presents a comprehensive review that focuses on recent research papers centred around deep learning-based and matrix factorization-based recommendation systems. The highlighted studies propose innovative methodologies and algorithms aimed at addressing the intricacies associated with recommendation tasks. The primary objective of this review is to provide a succinct overview of the pivotal contributions, employed techniques, and attained outcomes showcased in these studies.

The review begins by exploring the application of deep learning techniques in recommendation systems. Mishra and Rathi [29] utilize deep semantic structure modelling (DSSM) to develop a job recommendation system that effectively handles sparse data by representing job descriptions and skill entities using character trigrams. Sridhar et al. [30] propose an innovative approach for movie recommendation systems, leveraging deep learning and content-based filtering to enhance the recommendation process.

Shambour et al. [31] introduce a novel hotel booking recommendation system based on multi-criteria collaborative filtering, incorporating implicit user and item similarity, user similarity propagation, and user/item reputation to improve recommendation accuracy. Liu et al. [32] present a method that combines explicit and implicit feedback through a neural matrix factorization algorithm, addressing the limitations of existing deep learning approaches.

Wang [33] proposes a classification technique based on deep learning, incorporating word embedding and factorization machines to improve recommendation accuracy. Wang [34] focuses on developing a personalized recommendation system for tourism, addressing challenges such as sparse user data and the cold start problem.

Boppana and Sandhya [35] create a recommendation model that considers contextual information using deep learning techniques, TF-IDF, and a word embedding model. Balasamy and Athiyappagounder [36] developed a deep learning-based recommendation system for the e-learning industry, utilizing a content matrix and deep neural network for personalized recommendations.

Konstantakis et al. [37] propose a recommendation system that combines user preferences and cultural tourist typologies with collaborative filtering matrix factorization for tourism attraction. Chen et al. [38] utilize Funk Singular Value Decomposition (F-SVD), a Matrix Factorization technique, for rainfall estimation prediction.

Selvasheela et al. [39] introduce an approach for analyzing customer reviews by combining batch-normalized capsule networks with matrix factorization to address the maximum error-rate classification problem.

Li and Kim [40] propose an innovative recommender system for course selection, focusing on capturing user behaviours and course attributes to address the challenge of high-dimensional data sparsity. Pan and Chen [41] utilize a knowledge graph to learn user and item representations based on their relationships within the graph, effectively tackling the cold start problem.

Huynh et al. [42] introduce a novel filtering technique that incorporates lasso regression, combining similarity matrices derived from lasso regression and rating data to provide recommendations for new users. The researchers evaluate their method using well-known datasets such as MovieLens and Jester5k.

The reviewed research papers have shed light on the significant advancements and promising potential of deep learning-based and matrix factorization-based recommendation systems. These studies have addressed key challenges such as sparse data, cold start issues, and accuracy improvement by leveraging innovative methodologies and algorithms.

The application of deep learning techniques, such as deep semantic structure modelling, Monarch Butterfly Optimization, deep neural networks, and deep autoencoders, has proven effective in capturing complex patterns and enhancing recommendation performance [43].

Additionally, the integration of matrix factorization techniques has provided valuable insights into latent feature extraction and the relationships between users, items, and contexts [44,45]. The diverse domains explored, including job recommendations, movie recommendations, hotel bookings, tourism recommendations, e-learning, and more, highlight the versatility and applicability of these approaches.

This comprehensive review serves as a valuable resource, offering a deeper understanding of the recent advancements and inspiring further research and innovation in the field of recommendation systems.

3. Methods

The proposed method, ResNetMF, is a pioneering fusion of state-of-the-art matrix factorization and deep residual neural networks. It aims to address the limitations of matrix factorization, which excels with linear data but struggles with non-linear patterns. By harnessing the strengths of both techniques, ResNetMF aims to achieve more accurate learning of underlying data features and effectively handle non-linear patterns. Deep residual networks, initially developed for image recognition tasks, exhibit advanced abilities in identifying intricate patterns and capturing non-linear relationships, making them an ideal complement to matrix factorization.

The core concept behind ResNetMF involves the design of a neural network with multiple branches, each serving a specific purpose. This architectural configuration allows for the simultaneous utilization of matrix factorization and deep residual neural networks, enabling the capture of linear and non-linear patterns in the data. In the proposed model, distinct branches with unique architectures are constructed to extract specific features from the input data. Some branches use matrix factorization to identify linear patterns, which is highly effective with linear data. Matrix factorization decomposes the data into latent factors and captures linear relationships between users and items. Conversely, other branches employ deep residual neural networks, known for their exceptional performance in capturing complex non-linear patterns, particularly in image recognition tasks. These branches leverage convolutional neural network (CNN) variants that have successfully uncovered intricate features within visual data.

Combining these distinct branches, the model aims to leverage the complementary strengths of matrix factorization and deep residual networks. Matrix factorization excels at capturing linear relationships, while deep residual networks excel at detecting non-linear patterns. This integration empowers the network to handle both types of patterns effectively, resulting in a more comprehensive understanding of the underlying data. Instead of directly predicting the target score, the neural network adopted in ResNetMF focuses on estimating the error introduced by the matrix factorization model. This shift in focus is driven by the insight that improving the accuracy of the matrix factorization model can be accomplished by learning and predicting the discrepancies or residuals between predicted and actual scores. By effectively modelling and predicting these errors, the network refines the predictions made by the matrix factorization model, ultimately leading to more accurate recommendations.

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The matrix factorization model and the deep neural network are constructed as separate components within the ResNetMF framework. The matrix factorization model operates on the linear branch of the network, predicting initial scores based on linear patterns. Simultaneously, the deep neural network, functioning as a side branch, captures the non-linear residuals or deviations from the linear patterns predicted by matrix factorization. This arrangement enables the network to capture and learn the complex, non-linear relationships that matrix factorization may inadequately capture. An additional merging layer is introduced to consolidate the outputs of these two components. This layer combines the predictions from the matrix factorization model and the deep neural network, culminating in the final recommendation output. Various techniques, such as summation, concatenation, or weighted combination, can be employed within the merging layer based on the specific requirements of the problem.

The ResNetMF model presents a comprehensive and innovative framework that skillfully leverages the strengths of matrix factorization and deep residual neural networks to capture linear and non-linear data patterns. By integrating these approaches, the model significantly enhances the accuracy of recommendations by refining the predictions made by the matrix factorization model using the valuable insights captured by the deep neural network. This integration of linear and non-linear modelling significantly augments the network's ability to comprehend complex relationships within the data, ultimately leading to more effective and precise recommendations.

The proposed recommendation system eliminates manual data collection by leveraging matrix factorization to uncover hidden, latent factors within the data. Matrix factorization generates user and item feature vectors fed into the residual neural network by identifying linear data patterns. Instead, matrix factorization automatically extracts underlying information and generates user and item feature vectors. These vectors are then combined and input into the residual network, contributing to the prediction of user preferences. Moreover, the integrated residual deep recurrent neural network model with matrix factorization identifies hidden patterns within the input data and establishes connections between these patterns using deep neural networks. By overcoming the challenges associated with manual data collection, incorporating both latent and explicit factors, and generating additional features, the effectiveness of the recommendation system is significantly enhanced. The combined architecture of matrix factorization and residual network for recommendation tasks consists of two main components of matrix factorization and residual networks.

The Matrix Factorization component of the proposed approach consists of two key elements: User Latent Factors (U) and Item Latent Factors (I). The User Latent Factors matrix captures users' preferences and has dimensions equal to the number of users by the number of latent factors. It represents the underlying user characteristics that contribute to their preferences and choices. On the other hand, the Item Latent Factors matrix represents the characteristics of items and has dimensions equal to the number of items by the number of latent factors. It encapsulates the essential attributes and features of the items being recommended. The proposed approach effectively captures and leverages the latent factors associated with users and items, comprehensively representing user preferences and item characteristics within the recommendation system.

The Residual Network component of the proposed system consists of several essential elements. The Input Layer is the entry point, accepting input data, such as user and item features or other relevant contextual information. The Feature Extraction Layers, comprising multiple layers, perform convolutional, pooling, and activation operations to extract high-level features from the input data. These layers enable the network to learn and capture complex patterns and essential characteristics. The Residual Blocks, consisting of stacked convolutional layers and skip connections, are crucial in capturing residual information and facilitating deep learning. These blocks allow the network to leverage residual connections to learn more intricate representations effectively. The Global Pooling Layer aggregates the extracted features across spatial dimensions and produces a fixed-length feature vector, which encapsulates the essential information from the input data. The Fully Connected Layers, comprising one or more layers, further transform the extracted features, enabling higher-level abstraction and representation. Finally, the Output Layer generates the final recommendation scores

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or ratings, providing the ultimate output of the recommendation system. These components within the Residual Network component collectively work in tandem to extract meaningful features, facilitate deep learning, and produce accurate and informative recommendations.

This study introduces a novel equation that combines matrix factorization and residual networks for recommendation tasks. The equation is expressed as follows:

$$R = U \times I + F(X) \tag{1}$$

The proposed approach predicts the rating or recommendation score (R) by combining matrix factorization and a residual network. Matrix factorization uses user and item embedding matrices (U and I) to capture collaborative filtering patterns and represent user-item interactions. The residual network (F(X)) takes input features (X) and uses multiple layers to learn high-level features. The dot product operation (×) between U and I calculates the interaction between user and item embeddings. The addition operation (+) combines this interaction with the features learned by the residual network. This combined approach extracts meaningful patterns through matrix factorization and learns complex relationships and additional features through the residual network. By integrating these components, the system obtains the final recommendation score, leading to improved accuracy in recommendation systems.

The matrix factorization and the residual network are combined through the equation $R = U \times I + F(X)$. $U \times I$ represents the initial user-item interaction captured by matrix factorization, and F(X) represents the additional features learned by the residual network. The matrix factorization captures collaborative filtering patterns, while the residual network leverages input features to learn complementary features. The final recommendation score or predicted rating (R) is obtained by summing the matrix factorization interaction and the features from the residual network. This fusion of matrix factorization and the residual network improves the accuracy and quality of recommendations. In summary, the combined architecture of matrix factorization and the residual network offers a powerful and effective approach for recommendation tasks, enhancing accuracy and performance.

After the recommendation list, the system employs Natural Language Processing (NLP) techniques to analyze user queries and retrieve pertinent data. It emphasizes selecting information from the recommended list, considering user-specific needs. The selection process involves analyzing the user query, breaking it down into individual words, and examining reviews and descriptions associated with the recommended list. The item with the most matches to the user query is disseminated as the top recommendation. This process ensures efficiency by searching within a smaller set of examples generated by the recommendation system.

Three scenarios can arise during the item selection. In the first scenario, the item with the most matches is disseminated to the user, enhancing relevance and aligning with the user's query intent. The second scenario occurs when multiple items have equal matches. In this case, the item with a higher rank based on the recommendation order is prioritized. The third scenario occurs when no matching words exist or all items have equal word repetitions. In this situation, the first item in the recommendation list is disseminated as a default choice, providing a starting point for user exploration.

The recommendation list is crucial in guiding the system to determine which information should be disseminated. It considers user preferences, historical behaviour, demographic information, and contextual relevance. Dynamic reordering ensures that the most suitable options are presented prominently, increasing user engagement and satisfaction. This approach enables a more focused distribution of personalized and relevant recommendations, leading to higher user satisfaction, engagement, and conversion rates.

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4. Results

Two distinct datasets were utilized to evaluate the proposed ResNetMF method. The first dataset is a combined dataset from TripAdvisor, consisting of reviews, comments, attraction descriptions, and questionnaire responses. The widely recognized MovieLens dataset, known for its extensive collection of movie ratings, was also employed. Different datasets allow for a comprehensive evaluation of ResNetMF's performance across various dimensions. The MovieLens dataset is a benchmark for evaluating recommendation systems due to its large size and standardization. It enables rigorous testing of recommendation performance and the handling of vast data. However, it needs to fully capture the nuances of natural language processing (NLP) and user query analysis, which are integral to the proposed method.

In contrast, the Smart Kuching dataset provides textual information from user-generated content, such as reviews and attraction descriptions. This dataset enriches the recommendation process by enabling NLP techniques to analyze and match user queries with relevant textual content. It evaluates the ResNetMF method's capability in leveraging NLP for user query analysis and content matching. By incorporating these diverse datasets, the evaluation aims to provide a holistic understanding of ResNetMF's performance across different dataset sizes, characteristics, and the incorporation of NLP techniques. This comprehensive analysis robustly evaluates the method's effectiveness and suitability in real-world recommendation scenarios.

The creation of the first dataset involved meticulous curation, combining data from TripAdvisor and well-designed questionnaires. The MovieLens dataset serves as a well-established benchmark, offering a wide range of ratings for various movies. The decision to employ multiple datasets allows for a thorough examination of the ResNetMF method's performance under diverse circumstances, assessing its adaptability, scalability, and efficiency in processing large amounts of data. It also enables exploration of the method's strengths and limitations in different contexts, leading to potential improvements and refinements. Overall, using multiple datasets enhances the rigour and validity of the evaluation, providing a broader perspective on the capabilities and practical applicability of the ResNetMF method.

4.1. Evaluation Metrics

Mean Absolute Error (MAE) was chosen as an evaluation metric in this study for evaluation purposes. MAE quantifies the difference between predicted ratings and actual ratings provided by users, making it suitable for datasets primarily consisting of rating values. Similarly, Root Mean Square Error (RMSE) was employed as an evaluation metric, similar to MAE, to measure the difference between actual and predicted ratings. MAE and RMSE were used to estimate and recommend appropriate values for empty entries or ratings. In Equations (2) and (3), the symbol O denotes the set of pairs (a, b) where user a has provided a rating for item b.

$$\text{RMSE} = \sqrt{(1/(|O|)\ \textstyle\sum\_(a,b\ \in O)(T\_ab - T\_ab)\hat{}2\ )}, \quad (2)$$

$$\text{MAE} = 1/(|O|)\ \textstyle\sum\_(a,b\ \in O)|(T\_ab - T\_ab\ )|, \quad (3)$$

By utilizing these evaluation metrics, including MAE and RMSE, the study ensures a comprehensive assessment of the recommendation system's performance in delivering relevant and valuable recommendations to users.

4.2. Experiment 1

In the initial experiment, the MovieLens dataset was used, and the learning model underwent 15 epochs, where each epoch represented a complete iteration over the training dataset. The number of latent features, represented by K, was set to 10, and the dataset was divided into training and testing data, with 80% allocated for training and 20% for testing. The dataset was shuffled to distribute the rows between the training and testing sets to introduce randomness. The purpose of this study's experimental analysis is to comprehensively assess the performance of ResNetMF in comparison to other well-known algorithms such as Convolutional Matrix Factorization (CMF),

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Convolutional Neural Networks (CNN), and Matrix Factorization (SVDpp). The evaluation is based on two fundamental metrics commonly used in recommendation systems: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

The MAE performance results demonstrate the superiority of ResNetMF over CMF, CNN, and SVDpp. Among the methods, CMF achieved an MAE of 0.5977, SVDpp achieved an MAE of 0.6777, and CNN achieved an MAE of 0.6311. In comparison, ResNetMF showcased an impressive MAE of 0.5595, outperforming CMF by 6.96%, CNN by 11.45%, and SVDpp by 32.14%. These significant improvements highlight ResNetMF's capability to generate predictions closer to the actual ratings. The substantial reduction in absolute errors between the predicted and actual ratings attests to the effectiveness and accuracy of ResNetMF in the recommendation task. The evaluation of RMSE highlights the remarkable performance of ResNetMF compared to CMF, CNN, and SVDpp. Among the methods, CMF achieved an RMSE of 0.8038, SVDpp achieved an RMSE of 0.8853, and CNN achieved an RMSE of 0.8121. In contrast, ResNetMF achieved a commendable RMSE of 0.7361, outperforming CMF by 7.20%, CNN by 8.4%, and SVDpp by 15.57%. These substantial improvements emphasize the superiority of ResNetMF in reducing prediction errors and enhancing the accuracy of ratings. ResNetMF's ability to significantly minimize discrepancies between predicted and actual ratings is a testament to its effectiveness and reliability in the recommendation task.

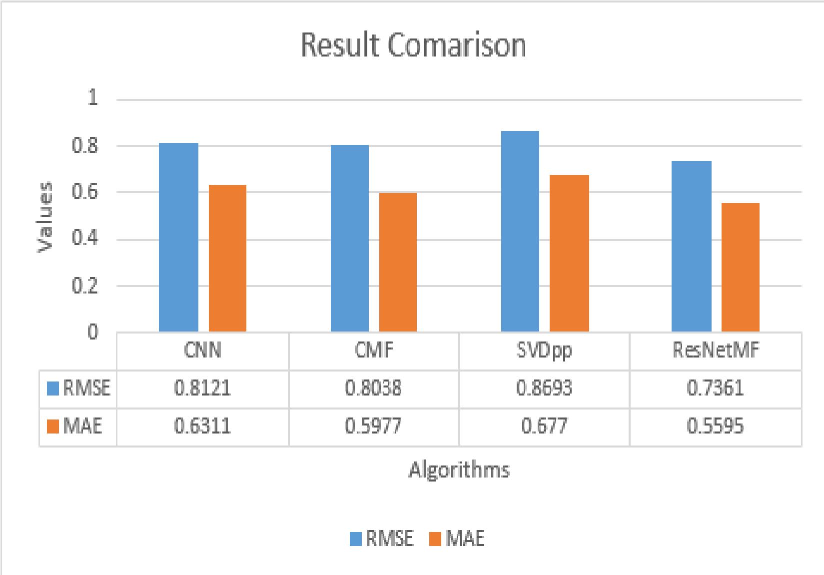

Figure 1. The Result comparison of RMSE and MAE of different algorithms with the proposed method.

The findings about the RMSE metric provide robust evidence of ResNetMF's ability to generate more accurate predictions and effectively minimize the errors associated with rating estimations. By consistently achieving lower RMSE values in comparison to the alternative algorithms, ResNetMF establishes itself as a highly reliable and precise recommendation model, offering superior performance and enhanced prediction accuracy.

The experiment involved comparing ResNetMF with benchmark algorithms like KNN and Coclustering. The results provided insights into the performance of these algorithms based on RMSE and MAE metrics. Among the baseline algorithms, SVDpp performed the best, achieving an RMSE value of 0.869 and an MAE value of 0.667 at its peak. However, ResNetMF achieved remarkable results, outperforming all other methods with higher scores in RMSE (0.736) and MAE (0.559). The table compares the MAE and RMSE values of the proposed method with other benchmark algorithms.

The experiments compared ResNetMF with other algorithms, and the results clearly showed that ResNetMF performed better in terms of MAE and RMSE values. The experiment result demonstrates that the proposed method is effective and accurate.

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Table 1. The proposed method result comparison with other algorithms.

Algorithm	RMSE	MAE
BaselineOnly	0.876	0.676
KNN Basic	0.958	0.735
KNN Means	0.906	0.692
KNN ZScore	0.904	0.686
KNN Baseline	0.882	0.674
SVD	0.879	0.677
SVDpp	0.869	0.667
NMF	0.935	0.7169
SlopeOne	0.911	0.696
CoClustering	0.952	0.737
NormalPredictor	1.422	1.136
ResNetMF	0.736	0.559

The experiments compared ResNetMF with other algorithms, and the results clearly showed that ResNetMF performed better in terms of MAE and RMSE values, which demonstrates that the proposed method is effective and accurate.

4.2. Experiment 2

For Experiment 2, we utilized the Smart Kuching dataset, dividing it into 80% for training and 20% for testing data. Similar to the previous experiment with the MovieLens dataset, the number of latent features, denoted as K, was set to 10. However, we observed higher RMSE values in this experiment. The disparity can be attributed to the sparsity of the Smart Kuching dataset, which contains a more significant number of missing ratings than the MovieLens dataset.

ResNetMF demonstrated exceptional performance compared to the baseline algorithms (CMF, CNN, and SVDpp) when evaluating both MAE and RMSE metrics. With an average MAE value of 0.7172, ResNetMF outperformed the other algorithms by achieving more accurate predictions with lower average error. In contrast, CMF had an average MAE value of 1.039, CNN had 1.08, and SVDpp had 1.5609. These results demonstrate the superiority of ResNetMF in minimizing the discrepancies between predicted and actual ratings, making it an excellent choice for recommendation systems utilizing the Smart Kuching dataset.

Additionally, ResNetMF obtained an average RMSE value of 1.2991, indicating its proficiency in reducing overall prediction errors. CMF had an average RMSE value of 1.4637, CNN achieved 1.460, and SVDpp obtained 1.951 on average. These findings further emphasize the exceptional performance of ResNetMF in accurately estimating user preferences and reducing discrepancies between predicted and observed ratings on the Smart Kuching dataset.

Furthermore, the proposed ResNetMF method showcased exceptional superiority over all baseline algorithms, delivering outstanding results with a peak RMSE of 1.144 and an MAE of 0.663. These remarkable performance metrics indicate ResNetMF's remarkable ability to make highly accurate predictions, surpassing the performance of all other evaluated algorithms. Notably, among the considered baseline models, the SVDpp algorithm demonstrated the highest level of accuracy, achieving a peak RMSE of 1.336 and an MAE of 1.082. These findings suggest that the SVDpp algorithm excels in predicting future time series data compared to the other baseline models. The results are visually presented in the following table to provide a comprehensive overview of the comparative performance.

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Table 2. The proposed method result comparison with other algorithms.

Algorithm	RMSE	MAE
BaselineOnly	1.474	1.286
KNN Basic	1.468	1.277
KNN Means	1.371	1.127
KNN ZScore	1.344	1.093
KNN Baseline	1.377	1.159
SVD	1.369	1.145
SVDpp	1.336	1.082
NMF	1.433	1.136
SlopeOne	1.413	1.179
CoClustering	1.391	1.12
NormalPredictor	2.5	2.113
ResNetMF	1.144	0.663

The experimental outcomes indicate the substantial influence of integrating ResNet into the matrix factorization procedure. This integration brings about noteworthy enhancements in the algorithm's performance.

The performance of the proposed method, ResNetMF, is evaluated on two datasets: the commonly used MovieLens dataset and the Smart Kuching dataset. The experimental results demonstrate that ResNetMF outperforms baseline algorithms by effectively capturing latent features that align with user preferences. It surpasses traditional matrix factorization methods like SVD, SVDpp, and NMF, as well as deep learning algorithms like CMF and CNN, in terms of accuracy and training speed.

The main drawback of existing baseline approaches is their inability to capture the latent dimensionality of the data [46,47], which limits their usefulness in supporting users' decision-making processes. In contrast, the proposed ResNetMF model addresses this challenge by leveraging cross-dimensional learning to identify relevant latent data structures that match user preferences, resulting in improved prediction performance and enhanced recommendations.

The proposed factorization method excels in discovering users' latent needs and preferences in large-scale recommender systems. It outperforms conventional matrix factorization methods by accurately describing users' preferences and identifying more latent factors that align with their preferences. These results highlight the superior performance of the proposed model compared to baseline methods while maintaining a comparable level of prediction accuracy.

Additionally, the integration of deep residual networks with matrix factorization enhances the overall performance of the algorithm. Applying residual networks to matrix factorization improves performance across all evaluation metrics. This observation underscores the potential of deep residual networks in boosting the effectiveness of matrix factorization algorithms.

ResNetMF method demonstrates superior accuracy compared to existing baseline techniques and other deep learning algorithms like CNN. It effectively identifies latent features that align with user preferences in large-scale recommender systems, achieving a better balance between precision and recall compared to baseline methods. The study also highlights the potential of deep residual networks to enhance the performance of matrix factorization algorithms. Overall, the evaluation results indicate that the ResNetMF approach holds promise for enhancing the accuracy and effectiveness of recommender systems and suggests avenues for further research in this field.

After generating the recommendation list, the system faces the task of determining which items should be presented to the users; therefore, simple Natural Language Processing (NLP) techniques are employed.

Measuring the dissemination performance of the recommendation system poses a unique challenge, unlike traditional benchmark measurements such as Root Mean Square Error (RMSE) that evaluate prediction accuracy. Since the final decision-making lies with human users and their

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cognitive processes, assessing the impact of this decision-making on the overall recommendation experience becomes challenging.

Given the complexity involved in measuring dissemination effectiveness, the study focuses on evaluating user satisfaction with the recommended results. A proposed method involves selecting 50 random users from the Smart Kuching dataset participants and requesting them to provide at least 5 queries to the system. These users are then asked to rate their satisfaction and perceived relevance of the results on a scale from 1 to 10, where 1 represents low satisfaction and relevance, and 10 represents high satisfaction and result relevance.

The study collected a total of 286 queries from users, resulting in an average rating of 7.25. This result indicates that, on average, 72.5% of the users expressed satisfaction with the disseminated information. These findings suggest that the recommendation system and the information selection process performed well, as most users found the recommended results satisfactory. However, it is essential to acknowledge the limitation of the study's small sample size of 50 users and the use of Kuching City attraction data, which may impact the generalizability of the results. Future research should include a more extensive and more diverse user sample to obtain more representative insights.

The study highlights the challenge of measuring dissemination performance due to the involvement of human decision-making in the recommendation process. It introduces a method for evaluating user satisfaction with the recommended results and reports a favourable average satisfaction rating of 7.25. The study acknowledges the limitation of the sample size and emphasizes the need for further research to validate the findings on a broader user base.

5. Conclusions

In conclusion, the proposed method outperforms all tested algorithms in terms of error measurement metrics, demonstrating its superior performance in handling complex problems such as sparse data or limited training samples compared to the baseline algorithms. Moreover, it provides more accurate and relevant recommendations to users, thereby enhancing the effectiveness of recommendation systems. The study adopts a deep learning approach with a streamlined architecture featuring a reduced number of layers compared to traditional recommendation algorithms to discover latent features efficiently. Through comprehensive evaluation of the same dataset, the proposed approach consistently surpasses alternative methods, highlighting the potential of deep learning techniques to capture intricate patterns and relationships between users and items. Furthermore, the information selection process of the recommendation system was analyzed, and a method for measuring dissemination performance was proposed, which involved asking users to rate their satisfaction with the system's recommendations. The results showed that 72.5% of the users were satisfied with the disseminated information, indicating that the recommendation system and information selection process performed well.

However, despite the successful performance of the proposed method, there are still areas for improvement in the recommendation aspect. One major limitation lies in the inadequate handling of the cold start issue, which affects both new users and items. Additionally, considering the involvement of multiple criteria in the study, the matrix factorization technique employed may not fully capture the subtle nuances of different user criteria. Therefore, future research aims to integrate a knowledge graph with the proposed method, which involves creating separate knowledge graphs for users and items, facilitating the incorporation of new items into the system and establishing connections between users based on demographic information for personalized recommendations. Furthermore, the integration of global and local factorization methods, inspired by techniques proposed by researchers from Wuhan University, is intended to enhance the multi-criteria system, enabling improved mining and identification of different user criteria. By incorporating these advancements into the proposed approach, significant advancements can be achieved in the performance of recommendation systems. In addition, upcoming research endeavours involve utilizing transformers to train the neural network by leveraging the gathered comments, reviews, and descriptions. This methodology is expected to yield significant enhancements to the system. The

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utilization of transformers to train the neural network with textual data, such as comments, reviews, and descriptions, offers considerable prospects for future investigations. This approach has the potential to enhance the system's performance by enabling it to learn from textual information and gain a deeper understanding of user preferences.

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