UNIVERSITAS AMIKOM YOGYAKARTA

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ICITISEE 2024

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In the 8th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE 2024)
"Applying Data Sciences and Artificial Intelligence Technologies for Enviromental Sustainability"

D. I. Yogyakarta (Indonesia)
August 29, 2024

ICITISEE

Yoga Pristyanto, S.Kom, M.Eng

The General Chair of 8th ICITISEE 2024

Neural Collaborative Filtering for Improved Tourism Destination Recommendation

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2024 8th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE) | 979-8-3503-6897-0/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICITISEE63424.2024.10730542

***Abstract*— This study evaluates the effectiveness of Neural Collaborative Filtering (NCF) in enhancing tourism destination recommendation. The researchers employed a methodology encompassing a comprehensive literature review, integration of user preference dataset, and the application of the NCF algorithm. The evaluation utilized MAE and RMSE metrics, demonstrating significant improvement compared to the Neural Network method. The results highlight the superior accuracy and reliability of the NCF-based recommendation system in providing tourism destination recommendation. This study emphasizes the practical significance of implementing NCF, offering a more sophisticated and efficient approach to enhancing user experience. The implication of this research contribute to academic needs and are expected to provide practical benefits for recommendation system in the tourism sector. The researchers elucidate critical differences in the NCF algorithm compared to benchmarks, and the introduction explores gaps in NCF applications for tourism, reinforcing the importance of this study. Experimental results show that the NCF model achieved an MAE of 0.306 and an RMSE of 0.371, outperforming the Neural Network's MAE of 0.794 and RMSE of 0.960, confirming superior predictive accuracy.**

Keywords*— *Neural Network, Neural Collaborative Filtering, Evaluation Metrics, Tourism Destination Recommendation

I. INTRODUCTION

Tourism has evolved from a mere necessity into an integral part of global society. Recommendation systems have become essential in enhancing travel experiences amidst complex travel dynamics. Digitalization has propelled these systems to the forefront, offering customized travel options. This aligns with the observations of [1] regarding the extensive influence of recommendation systems, leveraging artificial intelligence to enhance accuracy and adaptability.

In the context of tourism, Neural Collaborative Filtering (NCF) significantly improves recommendation accuracy and user satisfaction, as emphasized by [2]. By integrating collaborative filtering with neural networks, NCF meets the need for advanced and contextual recommendation systems in the ever-evolving tourism industry. This research addresses the challenges posed by increasing data and complex tourist preferences, offering advanced technological solutions to enhance the precision and personalization of tourism destination recommendation.

Machine learning, particularly Neural Collaborative Filtering (NCF), deepens our understanding of tourist preferences and behaviors. As explained by [3], NCF improves recommendation accuracy by utilizing artificial intelligence. In tourism, NCF can generate recommendation that consider individual preferences and complex consumer relationships. This potential makes NCF a valuable tool in tourism destination recommendation.

Sophisticated approaches are required to handle the complexity of tourist preferences and data. Advances in NCF technology enable more personalized and relevant recommendation, enhancing tourist satisfaction and trust. This research explores the practical implementation of NCF in tourism. It examines the potential of NCF to create better and more adaptive recommendation systems for tourism destinations.

This study explores and implements Neural Collaborative Filtering (NCF) to enhance tourism destination recommendation. NCF, which combines collaborative and neural network models, adapts to changing tourist preferences. By understanding consumer behavior and relationships, NCF generates more accurate recommendation. This approach aims to enrich the travel experience.

As stated by [4], NCF can improve recommendation accuracy and significantly enhance user satisfaction. This research examines the potential for performance improvements in recommendation systems. Additionally, it contributes to the understanding of NCF implementation in tourism, highlighting the benefits of using NCF to enhance tourism recommendation.

Previous research, as indicated by [5], demonstrates the success of NCF in various domains. However, the unique challenges of tourism require careful adaptation. This research proposes an optimized application of NCF to improve tourism destination recommendation. The goal is to fill knowledge gaps and contribute to the literature.

There is a lack of research on the implementation of Neural Collaborative Filtering (NCF) for recommending tourism destinations. While successful in other domains, the complexity of tourist preferences has not been well understood. This research aims to fill this gap by creating an enhanced NCF application for better travel recommendation. The objective is to improve understanding and application in the tourism context.

This research contributes in two main ways. First, it aims to provide a comprehensive theoretical understanding of NCF in tourism. By adapting this technology to the unique dynamics of consumer behavior, it offers a robust framework for creating more adaptive recommendation systems. Second, it addresses specific interaction patterns among tourists.

This research aims to fill knowledge gaps by presenting an optimized NCF application. It details the implementation steps and addresses specific challenges in tourism, offering guidance to researchers and industry practitioners. The goal is to improve the quality of destination recommendation systems. This research is expected to add value for stakeholders and support sustainable tourism growth.

II. RELATED WORK

Recommendation systems have become a significant focus of research in recent years, particularly in the context of commercial applications. The application of deep learning techniques in recommendation systems offers the potential to address various challenges faced by traditional collaborative methods. This article reviews the existing literature on the application of Neural Collaborative Filtering (NCF) and related methods in tourism destination recommendation systems and identifies existing research gaps.

A. *Collaborative Filtering Algorithms and Their Limitations*

Early research has highlighted the limitations of traditional collaborative filtering algorithms in addressing data sparsity and scalability issues. While these algorithms are simple and efficient, they struggle to enhance the quality of recommendation outcomes [2]. Other studies indicate that the application of deep neural networks to improve collaborative filtering algorithms can overcome these issues; however, further exploration within the context of recommendation systems is still needed [3].

B. *Integration of Deep Learning in Recommendation Systems*

Many studies have integrated deep learning techniques with collaborative filtering methods to enhance recommendation performance. Models such as Neural Collaborative Filtering (NCF) replace inner product with neural architectures capable of learning arbitrary functions from data, resulting in significant performance improvements in recommendation [3]. For instance, the J-NCF model combines deep feature learning and deep interaction modeling to optimize the recommendation process simultaneously, demonstrating substantial performance improvements over state-of-the-art methods [4].

C. *Application in Specific Recommendation Systems*

Although numerous studies have explored the application of deep learning methods in recommendation systems, several areas still require further attention. Research on the application of these methods in the context of tourism destination recommendation is still very limited. Related studies have predominantly focused on product recommendation such as movies, music, and restaurants, while the tourism destination context remains underexplored. Additionally, the combination of hybrid methods that integrate various recommendation techniques with deep learning also requires further exploration to identify the best combinations that can enhance recommendation performance [6] [7].

Research on the application of Neural Collaborative Filtering and deep learning techniques in recommendation systems shows promising results in improving recommendation performance. However, their application in the context of tourism destinations remains limited and requires further exploration. This research aims to fill this gap by applying NCF in tourism destination recommendation systems, offering the potential to provide users with more accurate and relevant recommendation.

III. RESEARCH METHODOLOGY

This research focuses on the application of Neural Collaborative Filtering (NCF) to enhance recommendation for nature tourism destinations in Indonesia. The dataset originates from a CSV file that provides details about various nature tourism destinations. Data preparation involved removing missing values and normalizing relevant features. Data processing steps included encoding categories using One-Hot Encoding for categorical features and standard scaling for numerical features. The data was then split into training (70%), validation (15%), and testing (15%) subsets to ensure fair model evaluation.

The NCF model was implemented using the TensorFlow library. Model parameters, such as the number of hidden layers and units per layer, were tuned using Grid Search with Cross-Validation. The Adam optimizer was employed with an initial learning rate of 0.001. Dropout was applied with a rate of 0.2 to prevent overfitting.

The validation strategy used K-Fold Cross-Validation with k=5 to ensure consistent results and high reproducibility. Model performance was evaluated using the metrics MAE (Mean Absolute Error) and RMSE (Root Mean Square Error). Additionally, Early Stopping was utilized based on performance on the validation set to prevent overfitting and optimize the number of training epochs.

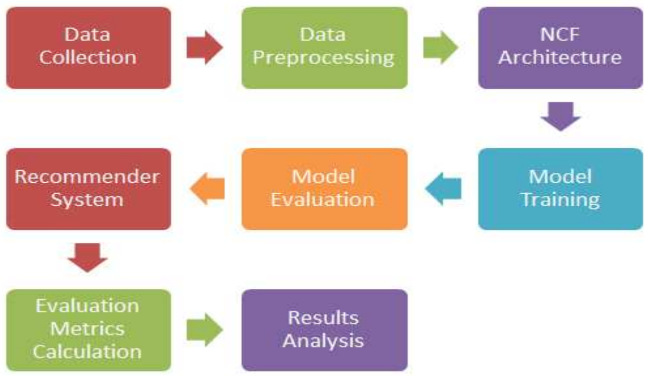

Fig. 1. The block diagram of research

Fig. 1 illustrates the block diagram of processing the tourism destination dataset using Neural Collaborative Filtering (NCF) to generate predictions and calculate the MAE and RMSE values. The dataset processing using NCF begins with collecting user preferences, ratings, and relevant features, followed by data pre-processing such as handling missing data and encoding categorical variables. The NCF architecture involves user and item embeddings, concatenation, a feedforward neural network, and an output layer. The model is trained using a dataset split into testing and training sets, utilizing backpropagation and optimization algorithms until convergence. Evaluation is conducted by predicting ratings for the test set and calculating MAE and RMSE. The recommendation system employs the trained NCF model to predict new ratings, rank destinations, and measure performance based on MAE and RMSE.

A. Recommendation System

Recommendation systems, a vital tool in the information age, address data overload by providing personalized content tailored to user preferences, thereby enhancing user experience in industries like entertainment, travel, and e-commerce. Collaborative Filtering (CF) predicts user preferences by analyzing similarities between users and items, while Content-Based Filtering (CBF) recommends items based on a user's past preferences. The integration of machine learning techniques, such as Neural Collaborative Filtering (NCF), further refines these systems, offering adaptive and precise recommendations. Collectively, these approaches improve user satisfaction and engagement across various domains [5].

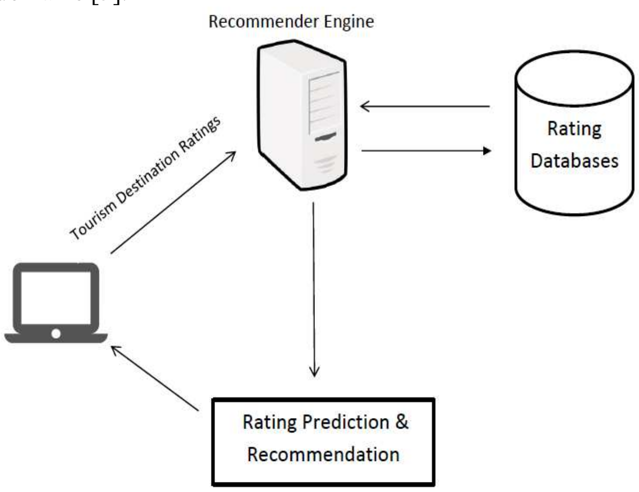

Fig. 2. Recommendation system

B. Neural Network

Neural networks (NN) have become powerful tools in recommender systems, significantly improving prediction accuracy and efficiency by capturing intricate patterns in user-item interactions, particularly with large and complex datasets. A central concept is the representation learning of user and item embeddings, which transforms features into dense, lower-dimensional vectors, capturing latent relationships crucial for accurate recommendations. Neural collaborative filtering further enhances this by combining collaborative filtering with neural networks, providing a more effective recommendation approach.

$$a_j = \sigma\left(\sum_{i=1}^{n} w_{ij} \cdot x_i + b_j\right) \quad (1)$$

Where a_j is the activation of the neuron, w_{ij} represents the weights connecting input x_i to the neuron, b_j is the bias term, and σ is the activation function.

C. Neural Collaborative Filtering

Neural Collaborative Filtering (NCF) revolutionizes recommender systems by integrating neural networks with collaborative filtering. This method improves precision and flexibility using latent representations and user-item interactions. NCF captures complex patterns and exploits user-item relationships, enhancing recommendation accuracy. Introduced by [3], it combines the strengths of both techniques for a more effective system.

The basic formula for the prediction in NCF is a feedforward neural network followed by the concatenation of user and item embeddings. In its simplest form, the prediction ($\hat{y}_{ui}$) for user u and item i can be expressed as:

$$\hat{y}_{ui} = f\,(\mathrm{MLP}([\mathrm{user\_embedding}_u, \mathrm{item\_embedding}_i])) \quad (2)$$

Here, user_embedding$_u$ and item_embedding$_i$ are the latent representations of user u and item i, and MLP denotes a multi-layer perceptron. The activation function f introduces non-linearity to the prediction.

D. The relationship between Neural Network and Neural Collaborative Filtering

The adoption of Neural Collaborative Filtering (NCF) over traditional Neural Networks (NN) is driven by its enhanced adaptability and improved ability to recommend tourism destinations. By integrating collaborative filtering with neural networks, NCF better captures user preferences and complex inter-user relationships, leading to more precise and customized recommendations. This methodology surpasses traditional NN models, offering a sophisticated, context-aware solution that adapts to diverse and evolving tourist preferences. The effectiveness of the NCF model is quantitatively assessed using MAE and RMSE metrics, ensuring precision and accuracy in the recommendation system.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |Y_i - \hat{Y}_i| \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=}^{n} (Y_i - \hat{Y}_i)^2} \quad (4)$$

Where n symbolizes the entire amount of observations, Y_i denotes the observed values, and Y_i represents the predicted values by the NCF model.

Through the use of these indicators, the study seeks to offer a thorough assessment of the suggested NCF model, offering insights into its ability to deliver precise and accurate tourism destination recommendation. The proposed methodology ensures a thorough examination of the model's performance against a benchmark, contributing to the advancement of recommendation systems in the context of tourism.

IV. RESULT AND DISCUSSION

A. Modeling

This research will utilize a publicly available dataset from the platform www.kaggle.com, recognized as the world's largest data science community. Kaggle has proven to be an invaluable tool for academics and data science practitioners, providing access to a variety of dataset, competitions, and discussion forums to facilitate knowledge exchange among professionals in the field.

To establish a solid theoretical framework for this research, a comprehensive literature review was conducted prior to any work being carried out. In-depth observations were also made to understand the context and characteristics of the dataset to be used. The findings from these initial stages form the basis for the analysis leading to model development, as depicted in Fig. 3.

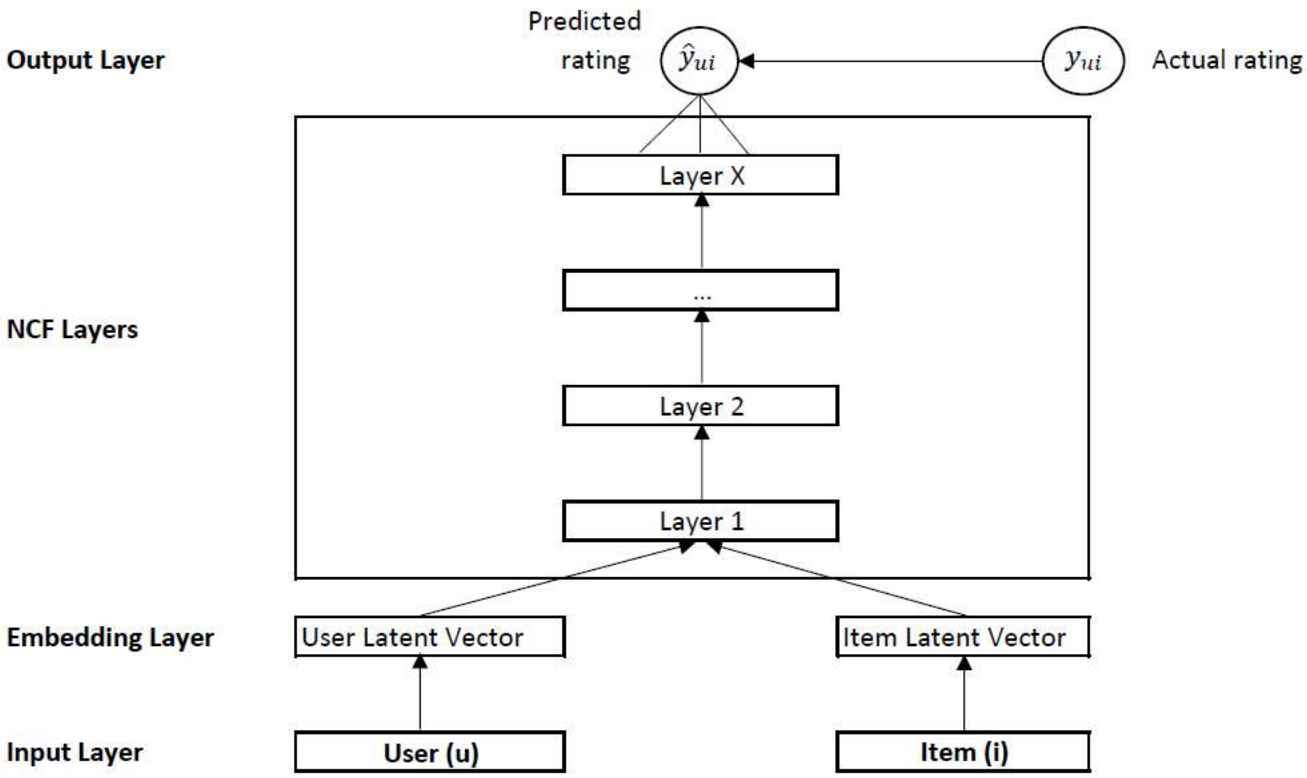

Fig. 3. Proposed model

The model developed in this research is grounded in key findings from the literature review and dataset observations, ensuring its relevance and robustness. By employing a rigorous, evidence-based methodology, this study aims to enhance the understanding of data science within the investigated context, providing a strong foundation for future advancements in the field.

B. Prototyping

This research analyzes "The Ecotourism in Indonesia" dataset from Kaggle to explore visitation patterns, preferences, and environmental impacts in Indonesian ecotourism, aiming to improve practices and understanding in the field [8].

TABLE 1. DATASET [8]

No	User_Id	Item	Item_Id	User_Rating
1	1	Saung Angklung Mang Udjo	28	2
2	1	Desa Wisata Ngadas	86	4
3	1	Taman Wisata Alam Punti Kayu	94	4
4	1	Hutan Pinus Pengger	146	3
5	2	Gunung Lalakon	17	2
6	2	Pulau Pramuka	62	3
7	2	Pulau Tidung	64	4
8	2	Air Terjun Semirang	103	4
9	2	Desa Wisata Kalibiru	137	4
10	2	Studio Alam Gamplong	178	4
…	…	…	…	…
837	155	Bumi Perkemahan Cibubur	56	4
838	155	Bukit Wisata Pulepayung	135	2
839	155	Kampoeng Rawa	112	4
840	155	Taman Hutan Raya Ngurah Rai	52	4
841	156	Dusun Bambu	15	5
842	156	Selasar Sunaryo Art Space	29	4
843	156	Goa Rancang Kencono	144	4
844	156	Setu Babakan	65	3
845	156	Taman Hutan Raya Ngurah Rai	52	4
846	156	Desa Wisata Sungai Code Jogja Kota	140	2

Table 1 presents a dataset detailing user ratings for various venues, including four columns: 'No' (entry number), 'User Id', 'Item', 'Item Id', and 'User Rating' . The ratings, ranging from low to high, indicate user satisfaction with each venue. The dataset includes ratings from 146 users across various locations, making it valuable for analyzing preferences. Collaborative Filtering techniques can use this data to suggest new venues based on user preferences.

Python was chosen for prototyping in this research, enabling efficient implementation and testing of concepts. Various libraries, such as numpy for numerical data, pandas for data analysis, matplotlib for visualization, and tensorflow, keras, torch, and sklearn for machine learning, were used. These tools supported the prototyping process.

C. Model Testing

The study compared the Neural Network and Neural Collaborative Filtering models by examining MAE and RMSE values over 100 iterations. The goal was to assess the effectiveness of Neural Collaborative Filtering in recommendation systems. Table 2 documents the results, providing insights into the models' accuracy and reliability. These findings inform optimal recommendation methodology deployment.

TABLE 2. THE EVALUATION METRICS

No	Model	MAE	RMSE
1	Neural Network (NN)	0.794	0.960
2	Neural Collaboration Filtering (NCF)	0.306	0.371

To facilitate the comparison of the two models presented in the table, the data is visualized in the form of a bar chart. This bar chart allows readers to observe the differences and similarities in the performance of both models more clearly and intuitively. Through the side-by-side bars, the heights representing values in each category can be easily compared, aiding in understanding the performance patterns and trends of both models.

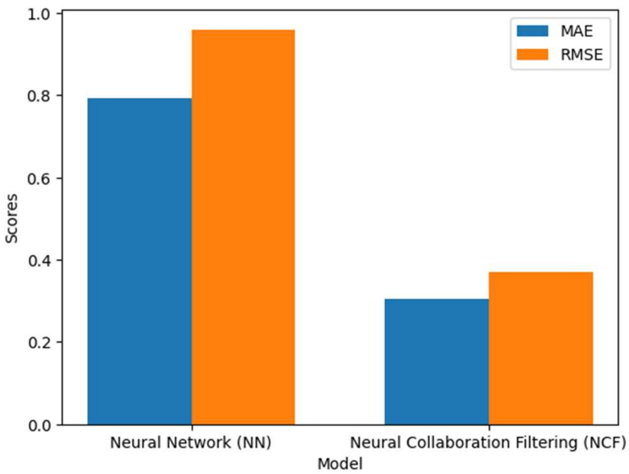

Fig. 4. MAE and RMSE Comparison of Models

Figure 4 shows a comparison of the models based on MAE and RMSE. The Neural Network (NN) model showed an MAE value of 0.794 and an RMSE value of 0.960, indicating a relatively high average prediction error. MAE measures the average absolute error, while RMSE places greater emphasis on larger errors. These values suggest that NN tends to produce less accurate predictions. Therefore, the NN model may be less ideal for use in contexts requiring high accuracy.

In contrast, the Neural Collaborative Filtering (NCF) model demonstrated significantly better performance with an MAE of 0.306 and an RMSE of 0.371. The lower MAE value indicates more accurate predictions, while the lower RMSE value suggests that large prediction errors are minimized. These results indicate that NCF is more effective than NN in predicting outcomes closer to the actual values. Therefore, the NCF model is more recommended for use in systems that require accurate and consistent predictions.

V. CONCLUSION AND FUTURE WORK

This study evaluates the effectiveness of Neural Collaborative Filtering (NCF) in enhancing tourist destination recommendation and compares it with Neural Network (NN) using MAE and RMSE metrics. The research demonstrates that NCF significantly improves the accuracy of tourism destination recommendation, yielding lower MAE and RMSE values compared to the Neural Network model. The tailored NCF algorithm performs better by handling the complexity of tourist preferences, highlighting the potential of NCF as a powerful recommendation engine in the tourism industry. Reducing MAE and RMSE values is critical for evaluating model performance, as lower values reflect increased accuracy. Experimental results reveal that the neural network model produces an MAE of 0.794 and an RMSE of 0.960, while the NCF model delivers much better results with an MAE of 0.306 and an RMSE of 0.371. These results confirm the superior accuracy of the NCF model in making predictions.

Given the promising results from utilizing Neural Collaborative Filtering (NCF) to enhance the accuracy of tourism destination recommendation, future research should strive to expand and deepen these findings. Additional experiments with larger and more varied dataset from different tourism sources could help ensure the generalization and robustness of the NCF model. Investigating the integration of supplementary features like weather data, user reviews, and social media trends could further improve the accuracy and relevance of recommendation. Testing the development of more advanced optimization techniques, such as hybrid models, might uncover additional performance improvements. Furthermore, implementing NCF in real-world recommendation systems and evaluating its effectiveness would provide valuable insights into its practical applications. Simplifying technical language and providing more intuitive explanations of the methodology and findings can make the document more accessible to a broader audience.

ACKNOWLEDGMENT

The authors acknowledge the invaluable financial support from the Education Fund Management Institute (LPDP) and the Education Financing Service Center (BPPT) of Indonesia. This funding was essential for acquiring necessary resources and conducting in-depth research. It highlights these institutions' commitment to advancing research and academic excellence. BPPT and LPDP's support was instrumental in making this study possible.

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