

Content-Based Restaurant Recommendation System Using the Best Match 25 Lucene (Bm25l) Method

Talitha Naifa Audrey

Universitas Airlangga, Indonesia

Email: talitha.naifa.audrey-2024@pasca.unair.ac.id

Abstract. Choosing a suitable dining place can be challenging for both locals and tourists due to the wide variety of culinary options and the limited availability of comprehensive recommendations covering food types, menu variations, prices, facilities, operating hours, and locations. To address this issue, this study aims to develop a Content-Based Restaurant Recommendation System Using the Best Match 25 Lucene (BM25L) Method in Pamekasan that assists users in selecting dining places aligned with their preferences. The system leverages the Best Match 25 Lucene (BM25L) method, which effectively accounts for document length in ranking, providing more precise recommendations. Data were collected from public sources such as Google and Instagram, complemented by direct field observations. System performance was evaluated through precision@k testing with 10 users, yielding a precision@10 score of 0.93 and a precision@20 score of 0.84. The results indicate that the most relevant recommendations typically appear within the top 10 positions, while relevance slightly decreases as the number of evaluated results increases. This demonstrates that the system is highly accurate for smaller result sets while maintaining acceptable relevance for larger sets. The research contributes to improving user experience by enabling faster and more reliable decision-making when choosing dining venues. Furthermore, the system provides a practical framework for future applications of content-based recommendation methods in the culinary domain and other service sectors. By prioritizing the most relevant options, this system enhances convenience, supports informed choices, and can serve as a model for similar smart recommendation solutions in regional tourism and hospitality contexts.

Keywords: recommendation system, BM25L, dining places, Pamekasan, Precision @k

INTRODUCTION

In today's modern era, food is an unavoidable part of human life. As time goes by, there are more places to eat, and more people choose to eat outside the house or at public eateries (Arief et al., 2012; Cholil et al., 2023; Muliadi & Lestari, 2019; Naufal et al., 2021; Oktavika, 2023; Suryadi et al., 2021). This kind of lifestyle has become a popular trend among the public. Many people are interested in finding a unique and interesting culinary experience. They love to try a variety of delicious foods and want to explore different places to eat (Jokom et al., 2025; Kaushal & Yadav, 2021; Seyitoğlu, 2021; Stone et al., 2018, 2022).

Diverse dining options often depend on several factors, including the taste of the food, the variety of menus served, the comfortable atmosphere, the attractive decorations, the availability of delivery services, the ease of online ordering, the prices offered, ratings, and the location, which serve as references in choosing a place to eat (Mishan et al., 2023). When one of these factors is well considered, it can attract the attention of visitors (Farid & Fitriannah, 2021).

In the Pamekasan area, there are a variety of dining options, ranging from street stalls to restaurants that serve various types of dishes. The variety of choices for places to eat and the lack of culinary recommendations—such as types of food, menu variations, prices, facilities,

operating hours, and different locations—pose challenges for local residents and tourists coming from outside the city or abroad in determining a suitable place to enjoy their desired culinary delights.

Given the problems faced by tourists and locals due to the lack of culinary recommendations, several previous studies have been conducted to address this problem, especially in the development of location-based dining recommendation systems. The results of these studies show that such systems make it easier for users to find places to eat by displaying recommendations based on the closest distance to the user's location. In addition, these systems also provide information such as addresses, phone numbers, opening hours, and closing hours.

Another study on BM25 discusses a summary of Indonesian noun-based documents, comparing the BM25 method, cosine similarity, and content overlap. Of the three methods, the BM25 method provides the best performance, with a maximum accuracy of 83%, compared to cosine similarity, which achieves 80%, and content overlap, which achieves 75% (Pinandhita, t.t.).

Other research has explored the BM25L method, including efforts to improve the legal information retrieval system by developing relevant feedback data sets. One study focused on the Brazilian House of Representatives, using 12 draft laws and 12 legislative consultations related to each query. In the BM25L model, documents were sorted by their relevance to the query. The "Conle" consultant provided feedback categorized as irrelevant, somewhat relevant, or highly relevant, with the restriction of retrieving the top 12 documents and setting the n -value (Kim et al., 2022).

Based on the topics discussed, the author recommends the application of the BM25L (Best Match 25 Lucene) method in a recommendation system for eateries in the Pamekasan area. The BM25L method itself is the best advancement derived from BM25. The BM25L method ensures that document length does not have an unbalanced effect on the ranking, resulting in more precise values when comparing food menus across dining places. The BM25L not only compares the menus of different places, but is also effective for ranking documents based on the queries used.

In this study, the food menu is used as the main factor. Meanwhile, the location, available facilities, price range, and the rating of the dining place are used as supporting factors in helping visitors choose a place to eat that suits their preferences. Thus, through the recommendation system using the BM25L method, users can easily find a place to eat that suits their preferences, enhance their experience in exploring the culinary world, and save time and effort when seeking their desired eateries.

From this background, the purpose of the study is to apply the BM25L method in the context of displaying dining recommendations in the Pamekasan area. The benefits of this research include providing a practical tool for users, both locals and tourists, to easily find dining options that match their preferences—thereby saving time and reducing decision-making uncertainty. From an academic perspective, the study demonstrates the application of the BM25L method in a real-world recommendation system, offering insights for future research on content-based recommendation models in the culinary and service sectors.

MATERIALS AND METHOD

A dining recommendation system that used the BM25L (Best Matching 25 Lucene) method was a system designed to recommend places to eat to users based on their preferences. The BM25L method was used to calculate the degree of compatibility between the query (user request) and the available restaurant data. This system typically involved the process of indexing and ranking documents, where the document referred to restaurant data related to the restaurant's name and food menu.

The main process in this system involved three main factors: Term Frequency (TF), TF Normalization, and BM25L. TF measured how often keywords (e.g., food name) appeared in restaurant descriptions, while TF normalization addressed the problem of document length imbalances. BM25L was used to calculate the ratings.

This recommendation system could provide recommendations for places to eat in accordance with the food menu in restaurants based on BM25L calculations. The analyzed restaurant data could include only food menus, while other information such as location, rating, and food prices served as complementary data. Thus, users could receive recommendations for places to eat that were relevant and suited to their preferences based on the ratings generated by the BM25L method. Here is a general summary for flowcharts.

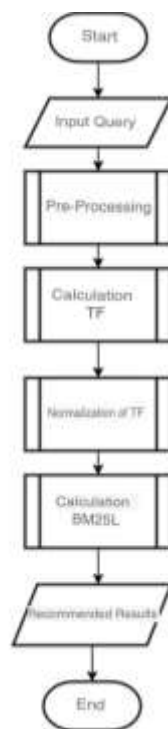


figure 1. flowcharts

To collect data related to the dining recommendation system using the BM25L method, the process started by gathering dining place data, including information such as restaurant names, locations, food menus, prices, and ratings. The author obtained the data sources through direct surveys at restaurants, searches on the Google site, the Instagram platform, and other public data sources. From the data that had been collected, the author tested five dining establishments, each of which had ten food menu items.

RESULTS AND DISCUSSION

The test device of this application is carried out using a laptop with certain hardware and software specifications. In terms of hardware, the laptop is equipped with an Intel(R) Core(TM) i5-8265U CPU @ 1.60GHz (8 CPUs) processor with a speed of ~1.8GHz, 8192 RAM memory, and an SSD with a capacity of 477 GB. Meanwhile, the software used includes the Windows 11 Home Single Language 64-bit operating system (10.0, Build 22631), Visual Studio Code, and the XAMPP Control Panel. At the implementation stage, this chapter presents the results of the implementation and testing of the dining recommendation system using the Best Match 25 Lucene (BM25L) method. The purpose of this implementation is to assess the BM25L's performance in displaying relevant recommendations and in accordance with user preferences based on the food menu. In addition, this chapter also discusses the application of BM25L on the website, the evaluation process carried out, and the analysis of the results obtained from the test.

Register View

This page is specifically designed to help users who don't have an account to create a new account easily. In the registration form provided, there are several sections that must be filled in by the user. These sections include email, password, and password confirmation. Users are required to enter a valid email address and create a secure password. In addition, users also need to fill in the password confirmation field to ensure that the password entered is correct and appropriate. By filling in all the required information correctly, users can successfully create a new account and start accessing the available services.

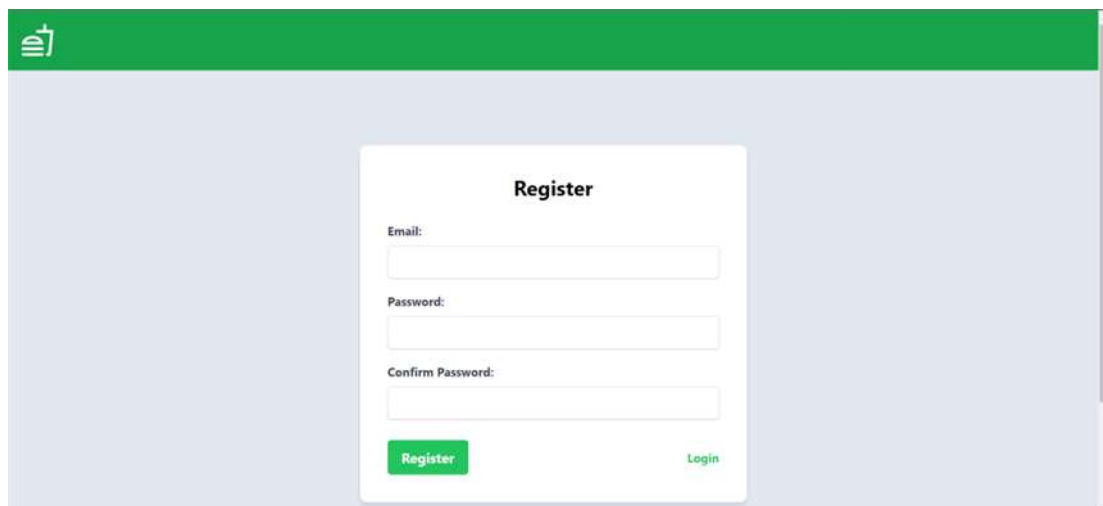
The image shows a web browser window with a green header bar containing a logo. The main content area is light blue and features a white rectangular form titled "Register". Inside the form, there are three input fields labeled "Email:", "Password:", and "Confirm Password:". Below these fields are two buttons: a green "Register" button and a green "Login" button.

Figure 2. Register

Login View

The login page is an important part of a website, where users can log in to their existing account to access the next page. The login process usually involves filling out a form with a pre-registered email address and password. The user must ensure that the information entered is correct and corresponds to the data stored in the system. After successfully logging in, users will be redirected to the next page that gives access to special features that are only available to users who have registered.

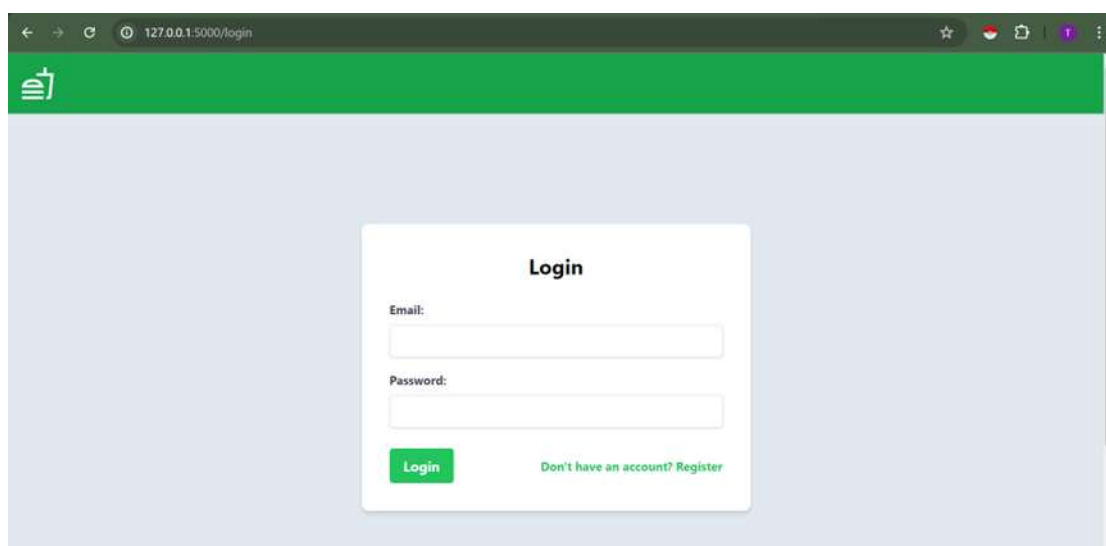


Figure 3. Login

Search View

This page is part of a website that is specifically designed to make it easier for users to search for certain content or information. By providing a search feature, users can enter relevant keywords or *queries* to find the information they need quickly and efficiently. Its function ensures that users can access various resources and data available on the website more easily.

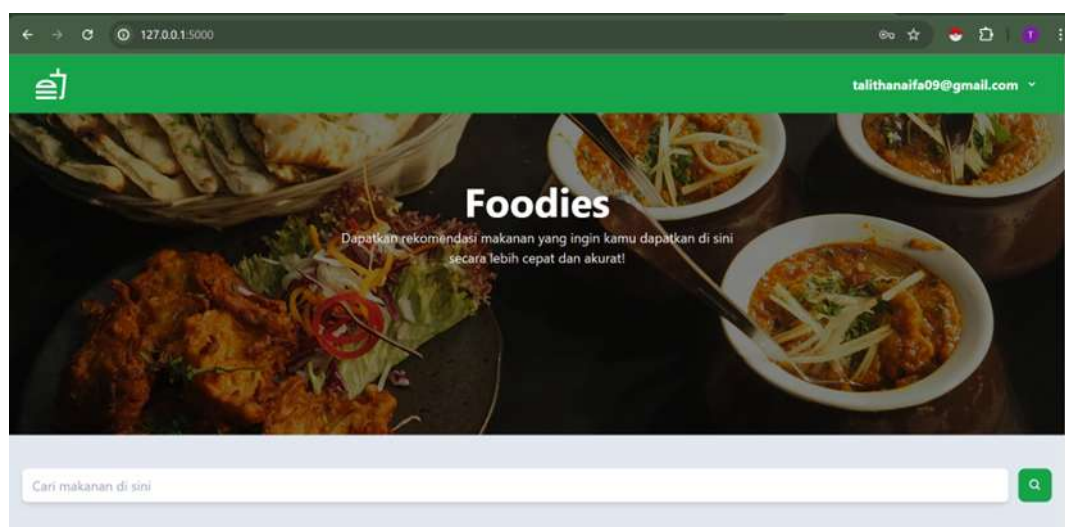


Figure 4. Search

Search Results Display

This view is the part of the user interface that displays relevant products or content based on keywords entered by the user. The goal is to make it easier for users to find the information they are looking for quickly and efficiently. Using the right view provides clear and structured search results, so users can easily identify and access the information they need without having to search for too long.

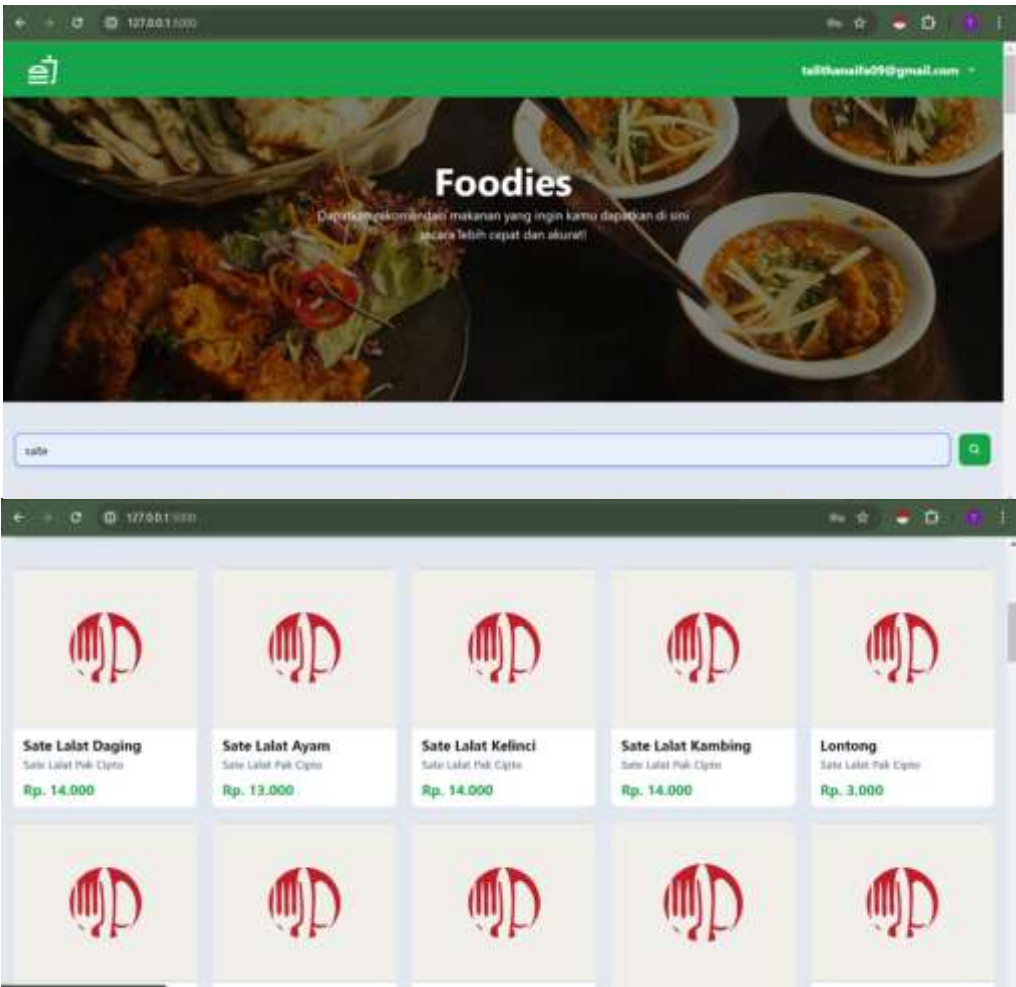


Figure 5. Searching Results

Recommendation Menu View

This page displays menus of recommendations based on what users searched for before. That way, users can see options tailored to their preferences and previous interactions. This makes it easy for users to find relevant content or products without having to search again from scratch every time they visit the page.

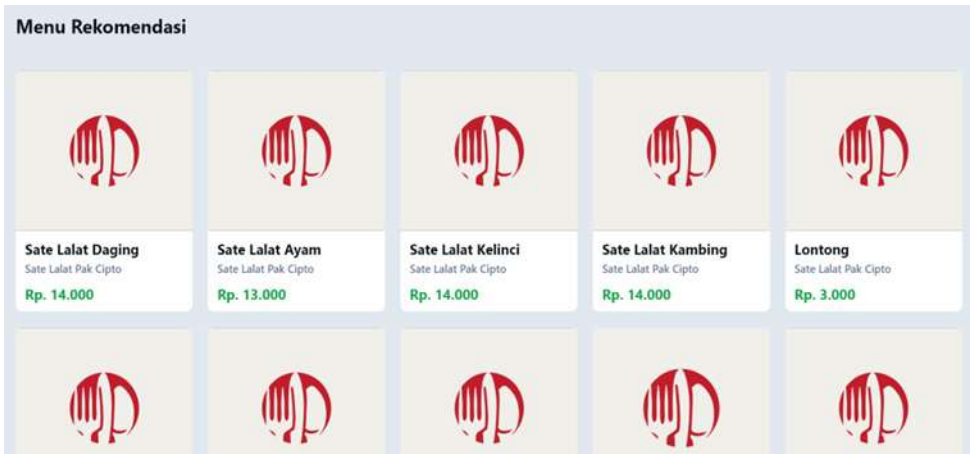


Figure 6. Recommended Menu

Detailed view of the dining area

Once users have selected their preferred dining place or menu, they will be redirected to a page that displays full details about the dining establishment. This page not only provides information such as the full address, hours of operation, and location shown on the map, but also a complete list of food and beverage menus and prices. Users can also view reviews from other customers that provide an overview of the quality of service and their experience at the restaurant. The information provided on this page is very helpful for users in making an informed decision about the places they want to visit. By having access to complete information. Users can more confidently choose a dining place that suits their preferences and expectations. This improves the overall user experience, ensuring that they can enjoy their visit without getting any unwanted things.



Figure 7. recommendation for eating places

System Test Results

In this study regarding the recommendation system for eating places, the main focus is the use of the BM25L method to improve the accuracy of the recommendation results. In addition, the test was conducted with a precision @K metric, where K represents the number of top rankings evaluated by the system. In this context, evaluations are conducted at $k = 10$ and $k = 20$ to assess the extent to which the system is able to provide relevant recommendations in the top 10 or 20 results using 1 word and 2 words. The following are the results of system testing that has been carried out by 10 users.

Table 1. Test Result 1 Word

Users	Keyword	K = @10	K = @20
Hanif	Chicken	1.0	1.0
Satya	Noodles	1.0	1.0
Fayi	Rice	1.0	0.95
Ilyas	Padang	0.7	0.35
Victor	Satay	0.8	0.9
Allan	Burger	1.0	0.8
Syifa	Orange Ice	1.0	0.9
Mitha	Meatballs	0.8	0.65
Laily	Juice	1.0	1.0
Reza	Matcha	1.0	0.85

Users	Keyword	K = @10	K = @20
Average		0.93	0.84

Table 2. Test Results 2 Words

Users	Keyword	K = @10	K = @20
Hanif	Fried Chicken	0.6	0.5
Satya	Fried Noodles	1.0	0.85
Fayi	Fried Rice	1.0	0.65
Ilyas	Padang Sauce	0.6	0.3
Victor	Chicken Satay	0.0	0.2
Allan	Small Burger	0.2	0.1
Syifa	Sweet Orange Ice	0.1	0.05
Mitha	Regular Meatballs	0.1	0.05
Laily	Soursop Juice	0.5	0.25
Reza	Matcha Latte	0.2	0.1
Average		0.42	0.305

For the calculation, take 1 user:

$$\text{Precision @10 for user 1} = \frac{6}{10} = 0,6$$

$$\text{Precision @20 for user 1} = \frac{10}{20} = 0,5$$

From the results of the calculation of precision @10 using 1 word, a value of 0.93 was obtained, while precision @20 using 1 word produced a value of 0.84. For the result of precision @10 using 2 words, a value of 0.42 was obtained and precision @20 using 2 words obtained a value of 0.305. One word is usually more focused and consistent, so the system can more easily find relevant results. While two words may have different or broader meanings, the results obtained are more diverse and less relevant. This difference in the value of k=@10 is greater than k=@20 this can be explained because more relevant results tend to appear in the initial rankings. The recommendation system has been optimized to display the most relevant results in ranks 1 to 10, so that the precision value is higher at k=10. However, when the number of results evaluated is expanded to 20, the average relevance of the overall results may decrease. This is because some of the additional results that appear after the top 10 may not be as relevant as those in the top 10, resulting in a decrease in accuracy at k=20.

This decline is natural and reflects how the level of relevance of results changes as the number of results evaluated increases. This shows the importance of focusing on initial ratings in improving the accuracy of the recommendation system, as well as the expansion of evaluations to understand the overall quality of the recommendations provided to users

The analysis highlights the importance of user behavior and interaction patterns in refining recommendation systems. Research by Herlocker et al. (2004) indicates that users often evaluate only the top-ranked recommendations, making early precision a critical factor for perceived system effectiveness, suggesting that continuous monitoring of user click-through rates and feedback can provide valuable data to iteratively improve the BM25L ranking weights. Adaptive tuning based on user preferences and query logs can enhance personalization, ensuring the system remains responsive to evolving tastes and local trends in Pamekasan's culinary scene. Additionally, Zhang et al. (2020) emphasized that integrating user interaction data with content-based ranking methods significantly improves the relevance of

top-N recommendations. Applying these findings to the BM25L system suggests that incorporating dynamic weighting based on user clicks, preferences, and query patterns could further optimize the recommendation output. Continuous analysis of user behavior, combined with content features such as cuisine type, menu variety, price, and location, ensures that the system adapts to evolving tastes and local trends, increasing engagement and satisfaction while maintaining high relevance in the initial displayed results.

CONCLUSION

This study successfully developed a content-based dining recommendation system for Pamekasan using the Best Match 25 Lucene (BM25L) method, where restaurant menu data served as the input for recommendations; the system was built with the Flask framework in Python. Implementation and evaluation using precision @k showed that single-word queries achieved higher relevance (precision @10 = 0.93 and precision @20 = 0.84), while two-word queries resulted in lower precision (precision @10 = 0.42 and precision @20 = 0.305), indicating that the system produced more accurate recommendations for single-keyword searches. For future research, it is suggested to explore multi-word query optimization or integrate collaborative filtering methods to enhance recommendation accuracy for more complex user preferences.

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