

Diversity enhancement in recommender systems with hidden Markov model integration

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Abstract

A significant influence on recommendation systems comes from the attractiveness of products in the current rating collection (RS). To lessen the recommendation model's bias, it is also necessary to address the diversity approach, which asks for adding less popular items to the list of ranked items during recommendation. Unlike traditional RS, the Recommender System filter's range of aspect-based enhancement may alter the user's dispersion ratio. This study presents a probabilistic approach to predict users' preferences when selecting carefully ranked items. In the suggested procedure, a list of 10 things is evaluated in order of popularity. In order of decreasing popularity, the first seven items are chosen for recommendations. The item's popularity and likelihood are calculated using the Hidden Markov Model (HMM). The last three options on the recommendation list are chosen from the less likely list, which is generated as well. The phases in the suggested technique are user interest pattern modelling, missing filling entry, and likelihood estimate using an HMM model. The findings of a comparison study using a graphical representation of user dispersion for the EDUA and CML parameters show that there are more users for less likely items when compared to modern methods.

Subject Classification: 68T05, 68P20.

Keywords: Hidden Markov model, Recommender system, Recommendation diversity.

1. Introduction

Recommendation Systems search through the enormous data available to discover pertinent, engaging topics and present them to

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consumers. Recommendations are generated by RS depending on the user's prior experiences. To find out about a user's historical actions, the Recommender system leverages temporal dynamics. There are several different recommendation algorithms that are used to produce relevant suggestions. Collaborative filtering (CF) is a widely used recommended technique.

Diversity and uniqueness are very important in RS. Most existing recommendation systems have a large number of users and items, but few functionalities. Every individual will consequently get similar or comparable recommendations. The personalized recommendation method may thereby increase consumer satisfaction. User reactions to tailored recommendations, such as more suggestions for items. Diversity increases the item coverage and gives all items in suggestions an equal opportunity. Tail items are not properly learned since there is not enough training data. The popularity criterion needs to be revised as a result. Non-popular products are contrasted with popular products to offer recommendations. All existing approaches fail to forecast tail items.

By taking into account stuff the user has never seen before, various types of suggestions are generated. A different set of thoughts is produced for each user. Therefore, it is important to focus more on creating tailored recommendations [18, 19, 22]. Long-tail or diverse recommendations are about items. Whether or not they are advised, consumers tend to consume the most well-liked products. On the other hand, a comfortable market demands that every item be kept under one roof. Users may now access all of the available product kinds in one location, which boosts customer satisfaction and store revenue.

To make a list of the top ten items, by selecting likelihood and less likelihood items using the Hidden Markov Model-based selection technique, in the user-specific suggestion list, the suggested method minimizes the diversity issue and increases the effectiveness of the recommendation system.

The main motivation of using HMM in the proposed technique is its ability to find sequential user behavior and latent preference dynamics which is required for accurate and diversified recommendations.

This paper's second section addresses various diversity methodologies proposed by many authors in the literature. The suggested work in section 3 provides a comprehensive approach to addressing diversity-related problems. Section 4 then includes the conclusion after covering the findings and analysis.

2. Related works

Enhancing recommendation rating and ranking quality is the primary goal of most current RS. The recommendations listed below are broadly grouped into following two categories:

Diversity Based Recommendation:

The Paudel et al. [1] examined algorithms that are accurate and efficient while providing a range of recommendations. These algorithms use random walks to sample the data. A substantial number of recommendations were also generated by the authors using The Ranking Method, a graph-based ranking recommendation system.

A unique notion of minimal average commonality based on negative evaluations and NN was presented by the Moody and Glass [2]. A novel user and item classification methodology was proposed by the author for the purpose of consumer-centered recommender system evaluation. The Chakraborty and Verma [3] of RS provided a variety of strategies.

A variety of recommendation problems are examined by Cheng et al. [4] using supervised learning to enhance diversity while maintaining accuracy. To evaluate the performance regarding accuracy and diversity, the authors developed a pairwise accuracy metric as well as a normalized topic coverage variety score. Using a deep learning network, non-popular service forecasting is possible (long-tail). The data sparsity issue is resolved by learning the user's preferred pattern. For the purpose of obtaining solid suggestions from unpopular suppliers, the deep learning model SADE is used by Bai et al. [5]. Recent e-commerce and marketing studies indicate that long-tail retailing will be more profitable for businesses in the future. To improve the quality of recommendations for goods and customers in the tail of the distribution, a combined regularization approach is proposed by Hu et al. [6]. It includes S-HMF to emphasize user preference specialization and C-HMF to emphasize user credibility.

The Antikacioglu and Ravi [7] created RS, which creates suggestions taking accuracy and diversity into account, and they examined the problem of developing diversity in CF-based RS. It is suggested by Liu et al. [8] to use CF to develop a novel combination recommendation approach that takes indirect social connections and matrix factorization into account. The model picks up new information by recording the preferences of individuals and traits of groups. To verify the model's effectiveness, experiments are carried out on sets of data from the real world.

A novel SeCM technique is paired with a core Borda count algorithm that emphasizes correctness by Xu et al. [9]. The authors demonstrated how exploratory behavior is motivated by curiosity. The authors carried out exhaustive tests with the provided datasets to assess the effectiveness of the recommended method. In this paper, the authors introduce an accuracy-focused module, a stimulation-evoked curiosity paradigm, and an assessment boost.

The continuation of an automatic playlist is offered using a mixed recommendation approach by Gatzoura et al. [10]. In the model, Case-Based Reasoning and Latent Dirichlet Allocation are employed. A relevant playlist is formed after semantic features are found. Precision and diversity are successfully combined in the suggested method.

Long-Tail Recommendation:

A unique learning strategy based on long-tail distribution and trust is provided to increase suggestion quality by Li, Liu, and Ren [11]. The user's appropriate neighbourhood is determined using the trust factor between users. The suggested model increases the predictability of ratings. An original strategy is proposed by Li et al. [12] to address both recent user recommendations and long-term recommendations. The suggested approach employs long-term projections to find a solution from scratch. The combined approach maximizes precision while reducing complexity.

The accuracy, diversity, and novelty of social-based RS were assessed by the Sacharidis [13]. It is suggested by Niu et al. [14] to use a suggestion technique to produce innovative and unexpected forecasts. In this instance, a two-step suggestion technique is used. The first step is to determine how people rank various items using user rating data. Diversity inclusion enhances recommendation performance.

A scalable and diverse recommendation approach is advised by Wang et al. [15] to be employed. The user receives a timely response when using the recommended method. Jang et al. [16] provided instructions on how to produce a range of suggestions. Tail-item sequential recommendation techniques are used to improvise the quality of recommendations. It is suggested that the approach improves the quality of recommendations for both popular as well as unpopular items. Furthermore, a problem with cold starts has been fixed.

Liu et al. [17] presents an innovative DC2B recommendation technique. The suggested method creates suggestions that take variety into account. A Bayesian recommendation framework is the DC2B.

Darvishy et al. [18] makes the case for a hybrid personalized news recommender system. The suggested methodology combines CF and content-based strategies. The scalability problem is resolved here. The clustering method boosts suggestion accuracy.

Cao et al. [19] proposes a varied recommendation issue. We predict missing data and provide predictions using a sparse tensor. The author coined the terms “recommendation novelty” and “recommendation coverage” to provide clarification on the recommender system. Zheng et al. [20] uses Graph Convolution Network (GCN) to demonstrate the importance of diversification. The authors revised their calculations of neighbour variety while coming up with suggestions to boost user happiness. The DGCN model under consideration yields insightful and varied recommendations.

The inventors of diverse recommendations, Liang et al. [21] concentrated on improving adaptivity at both the user and domain levels. In their suggestion for producing diverse recommendations, the writers addressed the variety of the individual. The intra-list distance and category coverage are used to assess the recommendation diversity. Gharahighehi and Vens [22] developed ways that use sequential rule mining to increase accuracy and variety. The writers gave things that promote diversity a higher weight in order to include diversity in their recommendations. The writers have employed a variable session-based RS.

Lin et al. [23] suggested a new re-ranking method to identify feature-based variety. By creating an aspect-specific ranking algorithm, relevance as well as diversity are balanced. Awati and Shirgave [24] spoke about the problem of data sparsity. The rating matrix's missing items were discovered by the authors utilizing matrix factorization. The suggested approach determines user trust through the clustering approach. Hsieh et al. [25] also suggested Collaborative metrics. Chhikara and Malik [27] developed a recommendation system using content based, collaborative filtering and knowledge based models to improve personalized user recommendations.

Present recommender systems only recommend popular goods. Things that are widely popular are extremely rare. There exist a multitude of unpopular products. This leads to a long-tail problem, where a large fraction of items are still not recommended. Alternatives that are always changing are available to users. The user therefore needs recommendations that are new and unexpected. Making original or distinctive recommendations can help to improve user satisfaction. Relationships that are indirect are crucial. The issue of cold starts is also covered in a number of suggestions. To improve the quality of both popular and

unpopular items, the recommendations should be made with more originality and diversity.

3. Proposed Work

One of the main components of recommendation systems (RS) is collaborative filtering (CF), which is necessary to increase user interest when sharing interactive information on online platforms. An essential psychological factor in the selection process is how things are ranked. Profitable pattern mining is well known for increasing business earnings by employing RS on e-commerce platforms. An important component of RS's platform strategy for accurate interest detection is the prediction of interest items based on popularity.

Items with lower popularity receive lower interest scores when histogram analysis is done. Consequently, the primary approach of the research presented here is the recommendation of a less common pattern, which is to increase the RS collaborative filtering.

Presumptions: The recommendation systems are biased because they choose the list of recommendations based on popularity.

The opposite of probability is the user's interest-based likelihood while choosing less well-liked goods.

Reducing the number of products in the list of recommendations generated for individual customers raises the possibility of profitable features on e-commerce platforms. The user's item distribution histogram might change if less popular items are chosen.

Undoubtedly, ratings from a variety of users affect the order in which goods are listed. Thus, in order to enhance the ranking of the items in RS, it is crucial to consider the pattern of interest, rating score, as well as user-shared criteria.

Awati and Shirgave [24] state that the trust-based paradigm is used to fill in the missing entries. Relation estimate can be used to characterize the problem of predicting whether a relationship will exist between a random pair of users for rating forecasting purposes. Based on how different item sets are rated, users may have a wide range of correlations. Consequently, considering how different correlations between user pairs can be predicted based on comparable rating structures.

The rating forecast is carried out by,

$$Ro, p = \sum_{g \in TNo\ to, g} rg, p / \sum_{g \in TNo\ to, g} \dots(1)$$

Where,

to, $g = S^*$, g is g th user in U which is a userset containing user o and item p .

Item numbers and their associated genres can be used to determine a user's interest pattern. Consider the movie dataset, which contains 100 items, each of which is connected to a specific genre. Thus, a number between 1 and 10 is assigned to the genre. This enhances the pattern representation style, making it easier to spot trends in user interest. As a result, Table 1 displays the interest pattern example, and Table 2 represents the genre number that corresponds to the interest pattern.

Table 1
User Interest Pattern

13	11	45	36	47	53	21	67	38	54
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Table 2
Genre Number

8	6	5	9	4	3	8	2	1	7
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The interest pattern of each user is a chained structure that makes sense logically. Thus, the comparable patterns are increasingly interested in common things, which indicates a growth in popularity. To determine the likelihood of patterns and the following items of interest, the Markov Chain Model idea can be used. The duration of the upcoming interest items may be modular. It is taken into account in this work with a length of ten items.

The Markov chain model for interest pattern is explained as follows:

The N interests" group

$$M = m_1, m_2, \dots, m_n \quad \dots(2)$$

A matrix of transition probabilities A

$$C = c_{11}, c_{12}, \dots, c_{v1}, c_{vn}, \quad \dots (3)$$

where each c_{vn} denotes the likelihood of switching from three interests v to interests m , such that

$$\sum_n m = 1 \quad c_{v m} = 1 \quad \forall v \quad \dots(4)$$

$P = p_1, p_2, \dots, p_n$ is a starting likelihood function over states. P_t represents the possibility that state t will start the Markov chain. Also,

$$\sum_t p_t = 1 \quad \dots(5)$$

In this case, the weight provided by the ranked structure is adequate to make product recommendations based on the probabilistic likelihood of various patterns. Consequently, our recommendation is based on the undeniable level of popularity of the items. To resolve “the diversity issue in RS, the less popular products will therefore be prioritized in the top 10 items utilizing a ranking structure. This makes selecting the” less popular option more likely, which raises the item’s popularity score overall. It is thus possible to observe that the profitable pattern has improved using this concept.

$$N \ 10Cr \quad \dots(6)$$

This implies that r possible combinations will be available for $N/10$ genres.

Let’s say that K displays patterns that are more common than r . $R-K$ patterns hence have fewer common combinations. K patterns must be changed in order to raise the popularity score of the less popular patterns.

One to seven ranked items from the l th pattern out of k patterns will be featured for each of the ten genres in each of the k patterns (which use regular RS-based ranked items). The final three items are less likely to be “chosen. If x is the likelihood calculated employing the HMM for the final three items in the chosen ranking, then the items with a likelihood of $1-x$ will be taken into consideration.

Step-by-Step Illustrative Example of Top-10 Recommendation Generation

To improve clarity, the working of the proposed algorithm using a single user example has been illustrated here.

Step 1: User Rating and Interest Pattern Formation

Consider a user u who has interacted with 10 items in the movie dataset. Each item belongs to a predefined genre class (numbered from 1 to 10).

- User interest pattern (item IDs): [13, 11, 45, 36, 47, 53, 21, 67, 38, 54]
- Corresponding genre pattern: [8, 6, 5, 9, 4, 3, 8, 2, 1, 7]

This chained genre sequence represents the user’s evolving interest behavior.

For example:

- The user initially shows interest in **Genre 8**,

- gradually shifts through **Genres 6, 5, and 9**,
- revisits **Genre 8**,
- and later explores **less-frequent genres** such as **1 and 2**.

This chained genre pattern serves as the **behavioral signature** of user u .

Step 2: Trust-Based Rating Prediction

Assume that user u **has not rated item p** , and this missing entry needs to be predicted.

If user u trusts three users with trust weights $[0.5, 0.3, 0.2]$ and they rated movie p as $[4, 5, 3]$ then:

$$R_{u,p} = (0.5 \times 4) + (0.3 \times 5) + (0.2 \times 3) / 1.0 = 4.$$

Thus, the missing rating entry for user u and item 36 is estimated as **4.1**, reflecting a **trust-weighted consensus** of reliable users.

Step 3: HMM-Based Pattern Likelihood Estimation

The genre sequence is modeled using a **Hidden Markov Model (HMM)**:

- **Hidden states:** Movie genres (1–10)
- **Observations:** User interactions
- **Transition matrix CC :** Probability of moving from one genre to another
- **Initial probability vector PP :** Starting genre preference

If:

- $C(8 \rightarrow 6) = 0.25$
- $C(6 \rightarrow 5) = 0.30$

then the model captures that users frequently transition from **Genre 8 to 6**, and from **6 to 5**.

Using P and C , the likelihood x of observing the full genre sequence is computed as:

$$x = P(g_1) \prod_{i=2}^n C(g_{i-1}, g_i) = P(g_1) \prod_{i=2}^n C(g_{i-1}, g_i)$$

Assume the computed likelihood:

$$x = 0.72$$

This indicates a **highly probable and common interest pattern**.

Step 4: Ranking Pattern Identification

All user patterns in the dataset are ranked based on their likelihood values.

- **Top-K high-likelihood patterns:** Popular and frequently occurring interests
- **Remaining R-K patterns:** Rare or under-explored interests

If:

- Total patterns $R=100$,
- $K=30$,

then:

- Top 30 patterns → **popularity-biased**
- Remaining 70 patterns → **long-tail preferences**

User u 's pattern with $x=0.72$ falls into the **high-likelihood group**.

Step 5: Top-10 Recommendation List Generation

To balance **accuracy and diversity**, recommendations are generated using **controlled probabilistic selection**:

- **7 items** from high-likelihood patterns (weight $x=0.72$)
- **3 items** from low-likelihood patterns (weight $1-x=0.28$)

This approach **reduces popularity bias** while still aligning with the user's core interests.

Proposed System Algorithm:

- Record of load ranking.
- Using eq. (1), apply trust-based ranking prediction for missing entry filling. By using genre classes of items, create rating-based patterns.
- Use the HMM model to calculate the likelihood (x) of every pattern in relation to the others.
- Look for the patterns with "likelihoods of one to three times.

- Make ten ranked items; choose the first seven with x likelihood and the remaining three with $1-x$ likelihood.

4. Experimental Result and Discussions

Experiments were conducted using five-star-rated MovieLens dataset (ml-latest-small) by MovieLens by Harper and Konstan [26], a movie recommendation platform. For 9,742 films, it currently has 100,836 ratings. This content was created with the help of 610 contributors with scores between 0.5 and 5.0. In order to create user interest patterns in the suggested model, each movie is linked to one or more genre labels.

The dataset was specifically examined and preprocessed according to item popularity in order to mitigate popularity bias and guarantee an impartial assessment of long-tail recommendation performance. The rating frequency histogram, or the quantity of ratings each item received, was used to calculate item popularity.

Two categories of movies were created:

Popular (head) items: Movies in the highest rating frequency percentile,

Movies with relatively low rating counts are considered less popular (tail) items.

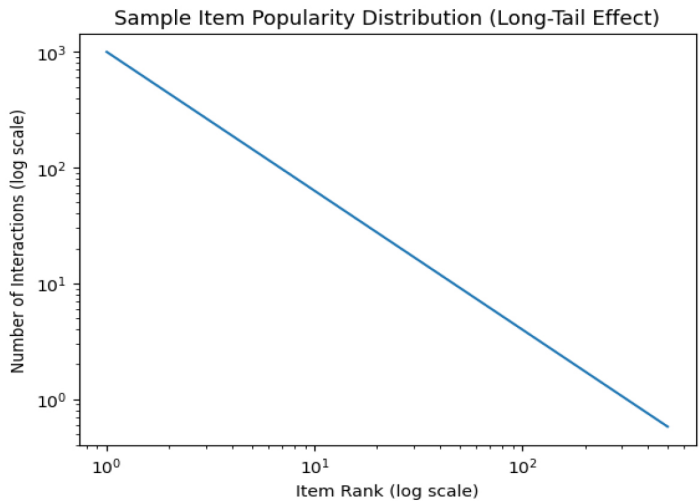


Figure 1
Item popularity distribution

As shown in the Figure 1, the long-tail behaviour indicates few popular items get lots of interactions while many items get very few interactions.

Evaluation Metrics

For conducting an extensive and diverse performance analysis, this method is evaluated in terms of accuracy as well as diversity. Complying with the suggestion from the reviewer, new parameters like NDCG, Coverage, and Novelty have been included in addition to existing parameters.

1. Normalized Discounted Cumulative Gain (NDCG)

The NDCG metric takes into consideration the relevance and position of the recommended items in the recommendation list. The higher the relevance of the items and their position in the recommendation list, the more the metric scores. The NDCG metric is therefore apt for the top-N recommendation challenge.

$$\text{NDCG@N} = \text{IDCG@N} / \text{NDCG@N}$$

This measures the ability of the proposed ranking approach in maintaining relevance along with diversification.

2. Coverage

Coverage is the degree to which the distinct items are represented in the lists of recommendations, showing the system's capacity to venture into the item space beyond the popular items.

$$\text{Coverage} = \frac{\text{Total number of items}}{\text{Number of distinct recommended items}}$$

3. Novelty

Novelty represents how unexpected or less popular the recommended items are to users. It is computed using the inverse popularity of items:

$$\text{Novelty} = \frac{1}{N} \sum -\log_2(\text{popularity}(i))$$

The comparison analysis, aided by the graphical depiction of user spread for the EDUA and CML values, shows how the suggested method tends to identify a larger number of unlikely or long-tail items than other approaches.

These experiments prove that the above framework is able to eliminate popularity bias and still preserve the quality of recommendations effectively.

Enhanced Domain-User-Level Adaptivity (EDUA)

Utilizing the probabilistic distribution of users at each probability level, the model is utilized to determine the user interest distribution.

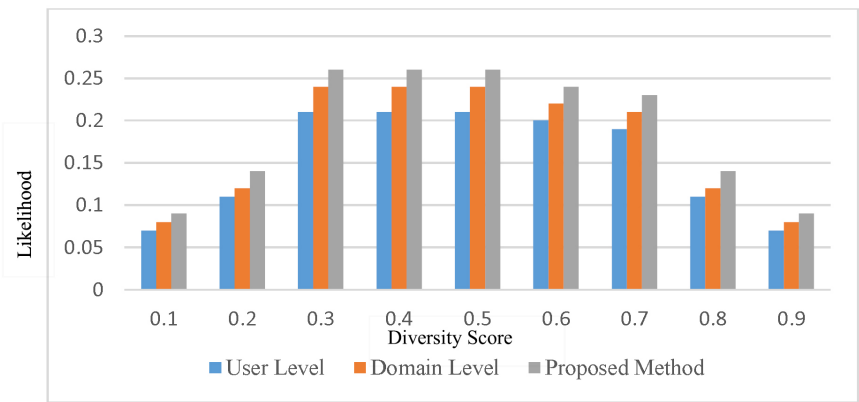


Figure 2

Enhancing “Domain level-User level Adaptivity Analysis Graph

Table 3

Analysis Report of Enhancing Domain level-User level Adaptivity

Diversity Score	User Level	DR_LT	Proposed Method
0.1	0.07	0.08	0.09
0.2	0.11	0.12	0.14
0.3	0.21	0.24	0.26
0.4	0.21	0.24	0.26
0.5	0.21	0.24	0.26
0.6	0.2	0.22	0.24
0.7	0.19	0.21	0.23
0.8	0.11	0.12	0.14
0.9	0.07	0.08	0.09

Collaborative Metric Learning (CML): CML learns a “joint user-item measure to capture item-item and user-user similarity as well as user preferences.

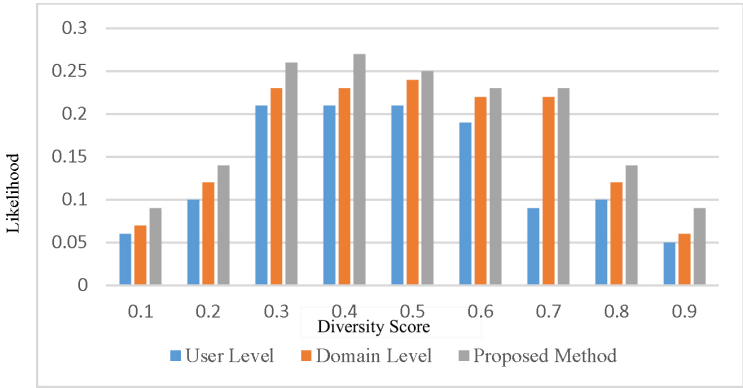


Figure 3
Analysis Graph of Collaborative Metric Learning

Table 4
Analysis Report of Collaborative Metric Learning

Diversity Score	User Level	Domain Level	Proposed Method
0.1	0.06	0.07	0.09
0.2	0.1	0.12	0.14
0.3	0.21	0.23	0.26
0.4	0.21	0.23	0.27
0.5	0.21	0.24	0.25
0.6	0.19	0.22	0.23
0.7	0.09	0.22	0.23
0.8	0.1	0.12	0.14
0.9	0.05	0.06	0.09

The effectiveness of two distinct criteria, EDUA and CML, is displayed in Tables 3 and 4, respectively. The graphical display also demonstrates that, in comparison to conventional approaches, the user’s distribution is broadened in terms of likelihood. The proposed approach trend may be seen expanding in Figure 2, and Figure 3.

5. Conclusion

In traditional RS, goods that move quickly or are in high demand are given prominence while users' suggestion lists are being created. Diversity issues result from this bias. The quantitative evaluation of the user's dispersion for item selection probability can be tracked in order to calculate the effectiveness of a given recommendation system. Enhancing the recommendation system's efficiency in reducing the diversity problem is the suggested HMM-based selection of high-probability and low-probability items for building a compilation of the initial 10 items in a particular user's list of suggestions. E-commerce pattern retrieval can be optimized in a way that gives each page on the website an equal degree of relevance for users. Collaborative learning, determinantal point likelihood graphs, and topic-wise-item level interest are all good examples of enhanced capabilities. This illustrates how considering less popular products in relation to the inversion of user probabilities can help e-commerce platforms become more profitable. In the future, more diversity-related initiatives could be implemented, which would increase the diversity of the recommendations.

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