Residual Temporal Coupled Matrix Factorization for Financial Asset Recommendation

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Abstract

Financial asset recommendation faces critical challenges: evolving investor sentiment and market conditions, popularity bias against less-traded assets, and complex asset co-occurrence patterns, which lead to poor recommendation quality and insufficient coverage of investors' needs. To address these issues, we propose residual temporal coupled matrix factorization (R-TCMF) that incorporates temporal regularization to capture temporal dynamics, coupled factorization leveraging normalized pointwise mutual information to model asset relationships, and residual factorization to counteract popularity bias. We then evaluate on the FAR-Trans, the first large-scale public financial transaction dataset. It shows that R-TCMF achieves 30.04% nDCG@10, 22.37% mAP@10, and 47.94% recall@10, representing improvements of 17.8%, 22.5%, and 12.9% respectively over the conventional approaches.

CCS Concepts

• **Information systems**; • **Collaborative filtering**; • **Computing methodologies**; • **Factorization methods**; • **Applied computing**; • **Economics**; • **Mathematics of computing**; • **Hypothesis testing and confidence interval computation**;

Keywords

Collaborative filtering, Financial recommendation, Popularity bias, Retail investors, Temporal matrix factorization

1 Introduction

The proliferation of financial technology has transformed how the retail investors access and interact with investment opportunities [1]. Modern investment platforms offer access to hundreds of financial instruments, from traditional stocks and bonds to complex derivatives and alternative investments. However, this abundance of choice creates a paradox: while investors have unprecedented access to diverse assets, they often struggle to identify investments

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that align with their preferences, risk tolerance, and financial objectives [2]. This challenge has motivated the development of personalized financial asset recommender systems (RS) that can guide investors toward suitable investment opportunities.

Financial asset RS requires capturing investor behavior patterns and suggesting relevant investment opportunities amid fluctuating market conditions. Classical collaborative filtering (CF) approaches—such as user-item matrix factorization (MF)—assume static preferences and often fail when preferences evolve or when item popularity skews recommendations toward frequently traded assets [3, 4]. Some existing financial recommendation studies rely on synthetic or proprietary datasets, limiting real-world applicability and generalizability due to the absence of suitable dataset [5].

To address these limitations, some researches have explored temporal extensions of MF. Koren's dynamic CF model incorporates time-dependent biases to track evolving preferences [3], while more recent temporal frameworks impose smoothness constraints on latent factors to handle sequential data [4, 6]. However, these methods typically ignore inter-asset relationships—critical in financial contexts where assets often co-move—and do not explicitly correct for popularity bias, leading to recommendations dominated by frequently traded instruments [7, 8].

The release of FAR-Trans, a large-scale, real-world financial transaction dataset, provides new opportunities for evaluating recommendation models under realistic market dynamics [9]. The dataset is extremely sparse (1.65% density), exhibits severe popularity bias (top 12 assets dominating over 50% of transactions), and reflects dynamic investor behavior (e.g., over 50% of investors executed less than 3 trades over 5 years vs. 650 power users with more than 100 trades each, and trade volume surges during COVID-19 volatility). Transaction logs further reveal strong asset co-occurrence patterns (e.g., bank stocks and government bonds frequently co-held). Some previous financial recommenders built without FAR-Trans used basic CF on synthetic data—omitting temporal coupling and asset co-occurrence modeling—serving as limited baselines [5]. We leverage FAR-Trans to develop and evaluate R-TCMF, integrating temporal smoothness, nPMI-based coupling, and residual bias removal to better model real investor behavior. Through extensive simulations, we demonstrate the following main contributions: (1) a framework that simultaneously addresses temporal dynamics, asset relationships, and popularity bias in financial recommendation, (2) evaluation on the first large-scale real financial transaction dataset, and (3) significant performance improvements with 17.8%, 22.5%, and 12.9% gains over the baseline across 3 metrics: nDCG@10, mAP@10, and recall@10.

The remainder of this paper is structured as follows. In Section 2, we review related work on collaborative filtering, temporal matrix

factorization (TMF), and popularity—bias mitigation in RS. Section 3 describes our methodology: Section 3.1 presents derive TMF from MF, Section 3.2 introduces temporal coupled matrix factorization (TCMF) that incorporates nPMI—based asset coupling, and Section 3.3 explains how residual factorization is used to correct popularity bias, yielding R-TMF and R-TCMF. In Section 4, we further introduce the characteristics of FAR-Trans and outline our experimental evaluation: Section 4.1 details the temporal rolling—window setup on the FAR-Trans dataset, and Section 4.2 lists the baselines, experimental protocols, and results. Finally, Section 5 concludes the paper and discusses possible directions for future works.

2 Related Works

Financial recommendation research has been historically constrained by limited data availability. Gonzales and Hargreaves [5] proposed a decision-support system using proprietary holdings and synthetic market data with basic CF and data-mining techniques, but lacked access to real transaction records. Asemi et al. [2] introduced an investment-type recommender combining investor profiles with expert feedback via ANFIS and neural networks, yet their evaluation depended on offline or simulated data rather than real transactions. Barreau and Carlier [10] applied history-augmented CF to financial products, but validation was limited to small proprietary datasets. Ghiye et al. [11] proposed time-decay functions for personalized CF in finance, improving over static CF but not addressing asset co-occurrence or popularity bias explicitly.

Modeling temporal dynamics is critical when user preferences or item characteristics evolve. Koren's seminal work on time-aware CF introduced per-user and per-item temporal biases learned from historical ratings [3]. Yu et al. [4] extended MF by enforcing smooth temporal transitions on latent factors for high-dimensional time series, demonstrating strong performance in seasonal recommendation contexts. Tahmasbi et al. [6] incorporated social ties and temporal coupling into collective MF, though focusing on social rather than financial recommendation. Bhavana and Padmanabhan [12] proposed a polynomial formulation for TMF enabling efficient latent factor estimation, yet without considering item coupling. Zheng et al. [13] explored learning-to-rank for financial asset selection with temporal features, but without explicit factorization of co-occurrence patterns.

Capturing asset relationships is crucial in financial contexts where co-purchase patterns reflect underlying economic connections. The use of nPMI to normalize co-occurrence has been advocated for collocation extraction in text [14], but most financial recommendation systems fail to leverage similar inter-asset dependencies. Pagliaro et al. [15] modeled investor behavior by analyzing financial advisor notes with machine learning, focusing on unstructured text rather than latent factor methods. Asemi et al. [2] combined investor profiles with expert annotations but did not factor in asset co-occurrence.

Popularity bias—the tendency to over-recommend frequently interacted items—reduces exposure to niche or emerging assets [7, 16]. Klimashevskaia et al. [7] surveyed methods to quantify and mitigate popularity bias, highlighting that simple popularity-based baselines can rival sophisticated models if bias is not addressed.

Elahi et al. [16] empirically evaluated user- and item-level bias in CF, showing that residual or debiased approaches substantially improve long-tail coverage. Carnovalini et al. [8] analyzed fairness in long-tail recommendations, advocating for explicit correction terms. In financial settings, popularity bias is particularly problematic as large institutional assets dominate transaction logs, obscuring opportunities in less-traded securities.

3 Methodology

Our framework development follows a progression of increasing sophistication. We begin with the foundational MF approach and extend its temporality, then enhance it by incorporating asset relationships that pure temporal models miss, and finally address systematic biases that can distort the underlying patterns we seek to capture.

3.1 Temporal Matrix Factorization (TMF)

The classic low-rank MF framework seeks to approximate an observed interaction matrix $R \in \mathbb{R}^{m \times n}$ by the product of two lower-dimensional factors:

$$R \approx UV^{\top} \tag{1}$$

where $U \in \mathbb{R}^{m \times k}$ and $V \in \mathbb{R}^{n \times k}$ encode the latent features of m users and n items; $k \ll \min(m, n)$ represents the chosen latent dimension; $R_{a,b} = 1$ if user a purchased item b at least once, 0 otherwise. The factor matrices U and V are optimized by minimizing a regularized squared-error loss over the set of observed entries $\Omega \subseteq \{1, \ldots, m\} \times \{1, \ldots, n\}$:

$$\min_{U,V} \sum_{(a,b) \in \Omega} \left(R_{ab} - U_a V_b^{\top} \right)^2 + \lambda \left(||U||_F^2 + ||V||_F^2 \right) \tag{2}$$

where $\lambda > 0$ controls the regularization strength and $|| \cdot ||_F$ denotes the Fresenius norm. This static model assumes temporal exchangeability that user preferences and item characteristics remain constant over time, which fails in financial applications where market conditions and investor sentiment evolve continuously, necessitating dynamic modeling approaches. Thus, we extend the classical framework with time-indexed factor matrices:

$$R^{(t)} \approx U^{(t)} V^{(t)\top}, \quad t = 1, 2, \ldots T \tag{3}$$

Here, $R^{(t)} \in \mathbb{R}^{m \times n}$ is the observation matrix at period t, and $(U^{(t)}, V^{(t)})$ are the corresponding time-specific latent factor matrices. To prevent overfitting and enforce smooth temporal evolution across the time that mimics real evolving user preferences and item attributes in financial markets, we introduce temporal coupling penalties that constrain consecutive time steps:

$$\begin{aligned} \mathcal{L}_{TMF}^{(t)} = \min_{U,V} \sum_{(a,b) \in \Omega} \left(R_{ab}^{(t)} - U_a^{(t)} V_b^{(t)\top} \right)^2 + \lambda \left(\left\|U^{(t)}\right\|_F^2 + \left\|V^{(t)}\right\|_F^2 \right) \\ + \gamma \left(\left\|U^{(t)} - U^{(t-1)}\right\|_F^2 + \left\|V^{(t)} - V^{(t-1)}\right\|_F^2 \right) \end{aligned} \tag{4}$$

where $\gamma > 0$ balances temporal smoothness versus model fit for $t > 1$, and $\gamma = 0$ for the initial period $t = 1$. We drive the optimization gradients for efficient parameter updates for any user p or any item q from the observed interactions:

$$\frac{\partial \mathcal{L}_{TMF}^{(t)}}{\partial U_p^{(t)}} = 2 \left[(\lambda + \gamma) U_p^{(t)} - \sum_{b|(p,b) \in \Omega} \left(R_{pb}^{(t)} - U_p^{(t)} V_b^{(t)\top} \right) V_b^{(t)} - \gamma U_p^{(t-1)} \right] \tag{5}$$

$$\frac{\partial \mathcal{L}_{TMF}^{(t)}}{\partial V_q^{(t)}} = 2 \left[(\lambda + \gamma) V_q^{(t)} - \sum_{a|(a,q) \in \Omega} \left(R_{aq}^{(t)} - U_a^{(t)} V_q^{(t)\top} \right) U_a^{(t)} - \gamma V_q^{(t-1)} \right]$$

$$(6)$$

3.2 Temporal Coupled Matrix Factorization (TCMF)

We introduce item coupling through co-occurrence matrices. Let $C^{(t)} \in \mathbb{R}^{n \times n}$ be the pointwise information (nPMI) matrices. Let $C^{(t)} \in \mathbb{R}^{n \times n}$ be the co-occurrence matrix defined as:

$$C_{ij}^{(t)} = nPMI \left(item_i, item_j | window\ t \right) = \frac{\log \left(\frac{p_{i,j}^{(t)}}{p_i^{(t)} p_j^{(t)}} \right)}{-\log \left(p_{ij}^{(t)} \right)} \quad (7)$$

where $p_{i,j}^{(t)}$ is the probability that items i and j co-occur in the same user transaction record during period t and $(p_i^{(t)}, p_j^{(t)})$ are their marginal probabilities. nPMI is chosen because its normalization to $[-1,1]$ yields comparable association scores that are well-suited for gradient-based optimization, avoiding the numerical instability that can arise from unbounded mutual information values. Moreover, while cosine similarity captures vector relationships effectively, nPMI's probabilistic foundation directly quantifies whether two assets co-occur more frequently than would be expected by chance. This probabilistic grounding helps distinguish genuine co-investment patterns (such as defensive assets clustering during market stress) from random noise. We couple the factorizations by sharing item factors:

$$R^{(t)} \approx U^{(t)} V^{(t)\top}, C^{(t)} \approx V^{(t)} V^{(t)\top}, \quad t = 1, 2, \dots T \quad (8)$$

This coupling ensures that learned item representations capture user preferences and inter-item relationships simultaneously. The joint optimization problem becomes:

$$\mathcal{L}_{TCMF}^{(t)} = \min_{U,V} \left[\sum_{(a,b) \in \Omega^{(t)}} \left(R_{ab}^{(t)} - U_a^{(t)} V_b^{(t)\top} \right)^2 + \alpha \sum_{(i,j) \in \Psi^{(t)}} \left(C_{ij}^{(t)} - V_i^{(t)} V_j^{(t)\top} \right)^2 \right] + \lambda \left(\|U^{(t)}\|_F^2 + \|V^{(t)}\|_F^2 \right) + \gamma \left(\|U^{(t)} - U^{(t-1)}\|_F^2 + \|V^{(t)} - V^{(t-1)}\|_F^2 \right)$$

$$(9)$$

where α is the coupling weight and $\Psi^{(t)}$ denotes the set of observed co-occurrence entries in period t. The gradient descent for $V^{(t)}$ incorporates both interaction and co-occurrence terms:

$$\frac{\partial \mathcal{L}_{TCMF}^{(t)}}{\partial V_q^{(t)}} = \frac{\partial \mathcal{L}_{TMF}^{(t)}}{\partial V_q^{(t)}} - 4\alpha \sum_{j|(q,j) \in \Psi^{(t)}} \left(C_{qj}^{(t)} - V_q^{(t)} V_j^{(t)\top} \right) V_j^{(t)}$$

$$(10)$$

3.3 Residual Factorization

To isolate genuine personalized preferences from systematic popularity bias, we consider two approaches.

3.3.1 Approach 1: Pre-computed Residuals. Define the popularity as the normalized transaction frequency:

$$Pop_i^{(t)} = \frac{total\ interactions\ of\ item\ i\ in\ period\ t}{total\ interactions\ in\ period\ t} \quad (11)$$

We then subtract popularities, employ the residual factorization, and add them back during prediction:

$$\tilde{R}^{(t)} \approx R^{(t)} - 1_m Pop^{(t)} \quad (12)$$

where $Pop^{(t)}$ is a row vector contains popularities of all items in t and 1_m is an m-dimensional vector of ones, creating a popularity-adjusted interaction matrix for factorization. This method is implemented on TMF and TCMF, leading to R-TMF and R-TCMF models.

3.3.2 Approach 2: Learnable Popularity (TimeSVD++ style). We let the model learn popularity jointly with latent factors:

$$R^{(t)} \approx U^{(t)} V^{(t)\top} + 1_m Pop^{(t)} \quad (13)$$

The optimization problem for Approach 2:

$$\mathcal{L}_{SVD++}^{(t)} = \min_{U,V} \sum_{(a,b) \in \Omega^{(t)}} \left[R_{ab}^{(t)} - \left(U_a^{(t)} V_b^{(t)\top} + Pop_b^{(t)} \right) \right]^2 + \lambda \left(\|U^{(t)}\|_F^2 + \|V^{(t)}\|_F^2 + \|Pop^{(t)}\|^2 \right) + \gamma \left(\|U^{(t)} - U^{(t-1)}\|_F^2 + \|V^{(t)} - V^{(t-1)}\|_F^2 + \|Pop^{(t)} - Pop^{(t-1)}\|_F^2 \right)$$

$$(14)$$

3.4 Algorithm and Theoretical Analysis

We present our general framework in Algorithm 1, where δ denotes the learning rate, $H^{(t)}$ is the binary mask of observed entries in $R^{(t)}$, $G^{(t)}$ is the binary mask of observed entries in $C^{(t)}$, $M^{(t)}$ is the binary mask vector for observed users, $N^{(t)}$ is the binary mask vector for observed items.

Algorithm 1 Unified Temporal Factorization Framework

Input: $R^{(t)}$ (replace with $\tilde{R}^{(t)}$ if using R-TMF or R-TCMF), $H^{(t)}$, $M^{(t)}, N^{(t)}, \delta, \lambda, \gamma, \alpha, (U^{(t-1)}, V^{(t-1)})$ if $t > 1$, $C^{(t)}$ if using TCMF or R-TCMF, $Pop^{(t)}$ if using TimeSVD++, $Pop^{(t-1)}$ if $t > 1$ and using TimeSVD++

Output: $U^{(t)}, V^{(t)}$, and $Pop^{(t)}$ if using TimeSVD++

Initialize: $U^{(t)}, V^{(t)}$, and $Pop^{(t)}$ if using TimeSVD++

repeat
  $e \leftarrow (R^{(t)} - U^{(t)} V^{(t)\top}) \odot H^{(t)}$
  if TimeSVD++ is enabled **then**
    $e \leftarrow e - 1_m Pop^{(t)} \odot H^{(t)}$
    $gp \leftarrow \lambda V^{(t)} - rowsum(e)$
  end if
  $gu \leftarrow \lambda U^{(t)} - e V^{(t)}$
  $gv \leftarrow \lambda V^{(t)} - e^\top U^{(t)}$
  if TCMF or R-TCMF is enabled **then**
    $r \leftarrow (C^{(t)} - V^{(t)} V^{(t)\top}) \odot G^{(t)}$
    $gv \leftarrow gv - 2\alpha r V^{(t)}$
  end if
  if t > 1 **then**
    $gu \leftarrow gu + \gamma(U^{(t)} - U^{(t-1)})$
    $gv \leftarrow gv + \gamma(V^{(t)} - V^{(t-1)})$
    if TimeSVD++ is enabled **then**
      $gp \leftarrow gp + \gamma(Pop^{(t)} - Pop^{(t-1)})$
    end if
  end if
  $U^{(t)} \leftarrow U^{(t)} - \delta(gu \odot M^{(t)})$
  $V^{(t)} \leftarrow V^{(t)} - \delta(gv \odot N^{(t)})$
  if TimeSVD++ is enabled **then**
    $Pop^{(t)} \leftarrow Pop^{(t)} - \delta(gp \odot N^{(t)})$
  end if
until stopping criteria met
return $U^{(t)}, V^{(t)}$ and $Pop^{(t)}$ if using TimeSVD++

Table 1: Ablation Study Results (increments relative to MF).

Models	nDCG@10(%)	mAP@10(%)	recall@10(%)
MF	25.50	18.26	42.48
Popularity	26.99 (+5.84%)	19.32 (+5.81%)	45.49 (+7.09%)
TMF	26.99 (+5.84%)	19.50 (+6.79%)	44.68 (+5.18%)
CMF	24.29 (-4.75%)	16.34 (-10.51%)	44.00 (+3.58%)
R-MF	27.88 (+9.33%)	20.18 (+10.51%)	46.03 (+8.36%)
TimeSVD++	24.40 (-4.31%)	16.84 (-7.78%)	43.21 (+1.72%)
TCMF	28.48 (+11.69%)	20.97 (+14.84%)	46.00 (+8.29%)
R-TMF	28.74 (+12.71%)	21.11 (+15.61%)	46.70 (+9.93%)
R-CMF	26.63 (+4.43%)	18.44 (+0.99%)	46.87 (+10.33%)
R-TCMF	**30.04 (+17.80%)**	**22.37 (+22.51%)**	**47.94 (+12.85%)**

The optimization problems in our framework are all non-convex due to the bilinear terms in either user-item or item-item factorizations. However, we observe that the training loss decreases monotonically and stabilizes within 300 iterations across most time windows, indicating empirical convergence to local minima, probably because the temporal regularization terms act as stabilizing constraints and the coupling weight is fine-tuned. Per-iteration complexity under the full R-TCMF framework is $O((|H^{(t)}| + |G^{(t)}| + |M^{(t)}| + |N^{(t)}|)k)$, where $|\cdot|$ denotes count of non-zero entries. Our framework mitigates overfitting risks through temporal smoothness penalties, coupled factorization, and residual correction. Furthermore, we also utilize bootstrapping to enhance the robustness of our results (section 4.2) in sparse regimes.

4 Experimental Evaluation

We conduct several experiments on FAR-Trans, the first large-scale public FAR dataset that comprises 29,090 anonymized retail investors and 806 tradable assets (321 with transaction history) over a nearly 4-year span (Jan2018–Nov2022). The raw data includes 703,303 daily price points and 388049 buy or sell events (sparsity ≈0.016%), recorded at daily granularity. Prior to release, the provider cleaned and aligned time series (deduplicating, imputing ≤10-day gaps, adjusting splits and currency changes) and normalized transaction logs (ensuring buy-sell consistency, mapping out-of-range dates to nearest trading day). All customer and asset identifiers have been irreversibly anonymized to protect privacy.

4.1 Temporal Setup

We adopt a rolling-window evaluation methodology to simulate real-world deployment:

- Learn the model parameters using binarized user-asset interactions from the preceding three-month window$\{t - 3, t - 2, t - 1\}$, and generate rankings for all possible user-asset pairs in the subsequent month t accordingly
- Mask the interactions that have appeared in the training window before scoring the testing results to ensure recommendations represent new investment opportunities and prevent trivial performance inflation

- Restrict evaluation to users who have at least one interaction both in the training window and in the next month to ensure fairness
- Measure performance against actual investments during period t according to nDCG@k, mAP@k, and recall@k, compute the average scores of all active users' recommendations
- Shift the evaluation window forward by one month and repeat the process across all available periods

4.2 Baselines and Experiments

To demonstrate the effectiveness of our R-TCMF model, apart from the TMF, R-TMF, TCMF, popularities, and TimeSVD++ that have been mentioned in Section 3, we also include association rule mining (ARM) [17], item-based KNN (IB KNN) [18], and user-based KNN (UB KNN) [19] as baselines. Furthermore, to validate the effectiveness each component, we also add coupled matrix factorization (CMF), residual matrix factorization (R-MF), and residual coupled matrix factorization (R-CMF) in ablation study. We employ bootstrap sampling to ensure stable hyperparameter selection across temporal variations:

- Generate 10 bootstrap samples (with replacement) from training data
- Perform grid search on each sample
- Use mode for categorical parameters and mean for continuous parameters
- Parameter ranges: learning rate is fixed at 0.00001 for all MF methods, initialization seeds: 114514 for $U^{(t)}$, 1919810 for $V^{(t)}$, 893 for $Pop^{(t)}$; maximum association rule length is set to be 3; regularization λ and γ, and coupling weight α: [0.01, 0.1, 0.3, 0.5, 0.7, 1.0]; latent dimensions k and neighbors: [5, 10, 15, 20, 50]; KNN similarity measures: *{Jaccard Similarity, Cosine Similarity}*

We assess recommendation quality using 3 complementary metrics and focus on the top-10 recommendations across 56 temporal splits: nDCG@10: measures ranking quality; mAP@10: assesses precision of relevant items; recall@10: quantifies coverage of actual investments.

The ablation study (Table 1) clearly illustrates the incremental benefits of each component, and their combination in R-TCMF delivers the most significant enhancement. It also shows that

Table 2: Statistical Significance Testing.

Models	nDCG@10(%)	mAP@10(%)	recall@10(%)
ARM	4.05 (p < 0.001)	2.09 (p < 0.001)	8.98 (p < 0.001)
UB KNN	23.25 (p = 0.004)	17.26 (p = 0.011)	36.02 (p < 0.001)
IB KNN	22.80 (p = 0.003)	16.52 (p = 0.005)	44.68 (p = 0.003)
R-TCMF	**30.04**	**22.37**	**47.94**

TimeSVD++ does not bring any positive enhancement compared to TMF, so we do not implement this on TMF and TCMF.

The statistical significance (Table 2) of these improvements is confirmed through block bootstrap testing with block length 5 and 10000 replications, where R-TCMF significantly outperforms traditional methods with p-values consistently below 0.05.

5 Conclusions and Future Works

This study introduces and evaluates R-TCMF framework for financial asset recommendation using the Far-Trans dataset. Key findings demonstrate that R-TCMF significantly outperforms both traditional collaborative filtering methods and TMF variants. The integration of temporal coupling penalties, nPMI-based item co-occurrence modeling, and residual factorization proved highly effective in addressing the core challenges of financial recommendation: evolving investor sentiment and market conditions, sparse interactions, and strong popularity bias. Our rigorous evaluation methodology employed bootstrap sampling for stable hyperparameter selection across temporal variations and block bootstrap testing to establish statistical significance, ensuring the reliability and robustness of our performance improvements. Despite these contributions, our work relies exclusively on a single dataset. Moreover, our approach focuses solely on modeling user preferences without incorporating crucial financial considerations such as portfolio profitability and risk management. Future research should address these limitations through validating across multiple datasets from diverse geographic and regulatory contexts, and integrating financial objectives beyond user preference modeling to better serve the complex needs of financial advisors and individual investors.

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