

# Semantic-Enriched Latent Factor Models with Sparse Data for Enhanced Performance of E-Commerce Recommender Systems

## Jaeni Jaeni

Doctoral Program of Information Systems, Postgraduate School, Universitas Diponegoro, Semarang, Indonesia | Department of Informatics Management, Universitas AMIKOM Yogyakarta, Sleman, Indonesia  
jaeni@amikom.ac.id (corresponding author)

## Purwanto Purwanto

Doctoral Program of Information Systems, Postgraduate School, Universitas Diponegoro, Semarang, Indonesia | Department of Chemical Engineering, Faculty of Engineering, Universitas Diponegoro, Indonesia  
purwanto@live.undip.ac.id

## Budi Warsito

Department of Statistics, Faculty of Sciences and Mathematics, Universitas Diponegoro, Indonesia  
budiwarsito@live.undip.ac.id

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## ABSTRACT

Recommender systems play a vital role in e-commerce by reducing information overload and providing personalized suggestions. However, conventional collaborative filtering methods often suffer from data sparsity and a limited ability to capture temporal user dynamics and user behavior. To address these limitations, this study proposes SEMAR-LF, a hybrid model that integrates Probabilistic Matrix Factorization (PMF), Long Short-Term Memory (LSTM), and semantic embeddings derived from product reviews. In this framework, textual reviews are preprocessed into semantic vectors, user-item interactions are temporally ordered, and sequential patterns are modeled through LSTM to generate dynamic user representations, which are then combined with item factors in the PMF framework for rating prediction. Experiments on the MovieLens ML-1M and ML-10M benchmark datasets show that SEMAR-LF consistently outperforms baseline models such as PMF, CTR, CDL, and ConvMF. The best performance was achieved on ML-10M with an RMSE of 0.79020, reflecting a 44.62% improvement over PMF in sparse conditions. As a complementary pilot, a lightweight SEMAR-ATT variant (PMF+RoBERTa-based content fusion) is presented that attains RMSE of 0.8565 and MAE of 0.6655 against a global-mean baseline (RMSE 1.0662 and MAE 0.8640), validating the effectiveness of semantic fusion even with simulated features. These results highlight the practicality and extensibility of semantic-enriched latent factorization for real-world recommendation systems.

*Keywords-collaborative filtering; probabilistic matrix factorization; e-commerce recommender system; word embedding; semantic regularization; contextual word representation*

## I. INTRODUCTION

During the past decade, e-commerce platforms have experienced rapid growth by utilizing Artificial Intelligence (AI)-based recommendation systems that incorporate Machine Learning (ML) and Deep Learning (DL). These systems can effectively address data sparsity issues, improving prediction accuracy and, consequently, user experience through personalized product customization [1]. Recommender

Systems (RSs) alleviate information overload, increase user engagement, and boost conversion rates. For example, recommendations make up roughly 80% of Netflix streaming activity [2], and Amazon obtains a substantial portion of its sales through its recommendation engine [3-5]. Four fundamental algorithmic strategies have emerged in e-commerce RSs: Collaborative Filtering (CF), knowledge-based recommendation, demographic filtering, and content-based filtering. These models represent distinct approaches that

generate personalized suggestions using different types of user data and item attributes [6-8].

Traditional CF techniques face the data sparsity problem and new user/new item problems resulting from the limited number of user-item interactions, which ultimately reduces the effectiveness of recommendations [9]. In practice, e-commerce needs recommenders that remain accurate under sparsity while adapting to temporal drift and leveraging rich textual feedback (reviews). To overcome these challenges, researchers have proposed hybrid methods that combine CF with content-based filtering, using both user data and item characteristics simultaneously [10].

Classical latent-factor models, such as Probabilistic Matrix Factorization (PMF) and Singular Value Decomposition (SVD), are foundational in collaborative filtering. However, although they offer high scalability, their performance significantly degrades under conditions of severe data sparsity. Furthermore, these models do not natively incorporate temporal dynamics or semantic signals, and extensions designed to handle time have confirmed the need for explicit temporal modeling beyond standard matrix factorization frameworks [11]. Models like Neural Collaborative Filtering (NCF) and sequential recommenders such as GRU4Rec, SASRec, and BERT4Rec excel at capturing item order and complex contextual dependencies. However, this enhanced capability typically incurs higher computational costs for both training and inference, primarily due to the use of recurrent or self-attention mechanisms. Their effectiveness also depends on the availability of sufficiently long and informative user interaction histories, which makes them less robust in extremely sparse settings [12-14]. Graph-based methods, such as LightGCN, leverage high-order user-item connectivity but introduce message-passing overhead and remain sensitive to long-tail sparsity [15]. These gaps motivate the proposed probabilistic hybrid approach that integrates semantic and temporal information for rating prediction under sparsity.

This work focuses on rating prediction in settings characterized by substantial sparsity of user-item interactions. Motivated by the limitations of classic CF in handling sparse interactions and evolving user preferences, SEMAR-LF is a hybrid framework that combines: (i) PMF, (ii) temporal user modeling via LSTM, and (iii) semantic regularization from review texts. The contributions of this approach are threefold: (i) semantic-enriched latent factorization that aligns latent factors with semantic signals to mitigate sparsity, (ii) temporal modeling that captures preference dynamics, and (iii) comprehensive empirical validation on ML-1M, ML-10M, and AIV, demonstrating consistent gains over strong baselines. In addition, a lightweight SEMAR-ATT (PMF+RoBERTa-based content fusion) model is proposed, demonstrating that content infusion remains effective even in a simplified fusion head. SEMAR-ATT is positioned as a pilot ablation compatible with the SEMAR-LF pipeline and as a stepping stone toward more advanced attention mechanisms.

## II. RELATED WORKS

CF remains the primary foundation in RSs with traditional methods such as SVD, which reduces dimensions through

latent factors but cannot use semantic insights [11], and PMF, which introduces a probabilistic approach to handle data sparsity [16]. Approaches such as CTR represent a hybridization, where topic modeling is fused with collaborative filtering to capture both thematic and latent user-item interactions [17]. Advanced DL approaches, such as ConvMF, integrate CNN with MF to extract high-level content features [18], while LSTM-PMF captures user temporal patterns [19]. In recent years, RNNs have garnered considerable attention due to their ability to capture temporal patterns in user-item interactions, thereby enhancing the accuracy and effectiveness of RSs [20].

Furthermore, LSTM-PMF [16] addresses temporal modeling by combining recurrent architectures with matrix factorization to capture user behavior over time. SVD++ [19] enhances basic SVD by incorporating implicit feedback into latent representations. Item Taxonomy-aware PMF (IT-PMF) [20] utilizes hierarchical item information to mitigate sparsity. Graph-based approaches, such as SVD-GCN [21], leverage Graph Convolutional Networks (GCN) to extract high-order user-item dependencies. FeatureMF [22] improves MF by embedding explicit features directly into the latent space. In addition, Time-aware Factorization Models (TAFM) [23] and Hybrid Matrix Factorization (HMF) [24] introduce mechanisms to model temporal drift and fuse auxiliary information, respectively, enabling more personalized and context-aware recommendations.

These diverse methods underscore the ongoing efforts to enhance the accuracy and contextual relevance of RSs. However, integrating semantic insights from textual content with temporal modeling in sparse environments remains a critical research direction that this study aims to address. Table I provides a synopsis of existing research, emphasizing the shift from conventional model-based methodologies to hybrid models.

TABLE I. OVERVIEW OF COLLABORATIVE FILTERING ALGORITHMS

Method	Description
SVD [11]	The user-item interaction matrix is decomposed into latent factors representing users and items.
PMF [16]	Model item interactions probabilistically to handle sparse data.
LDA [21]	Thematic structures are extracted from the text to analyze product reviews.
CTR [17]	Integrates topic modeling with collaborative filtering to improve rating forecasts.
CDL [22]	The content information and collaborative signals were modeled using deep learning.
ConvMF [18]	CNNs use matrix factorization to combine and extract item content features.
LSTM-PMF [19]	LSTM networks are combined with PMF for modeling sequential user behavior.
SVD++ [23]	Extends SVD by incorporating implicit feedback to improve user preference modeling.
IT-PMF [24]	Integrating item taxonomy with PMF to enhance recommendations in sparse conditions.
SVD-GCN [25]	Combines SVD with graph convolutional networks to capture complex user-item relationships.

Recent studies have enhanced hybrid RSs by combining semantic embeddings with temporal modeling. Approaches such as NCF [26] capture contextual dependencies in sequential data, while time-aware models [27] improve accuracy but often suffer from high computational costs, a dependency on complete feature sets, and limited semantic integration, which restricts their ability to fully exploit contextual information from textual data. Similarly, trust-aware POI recommendation has been advanced by integrating heterogeneous behavioral signals, as demonstrated in [28], where the ITCRC model combines ratings and check-ins to infer implicit trust, thus reducing sparsity and improving the quality of the recommendations.

Textual reviews provide rich semantic signals that can be fused with collaborative factors to mitigate sparsity. Early review-aware hybrids, such as ConvMF, integrate CNN-based document features into PMF, while DeepCoNN [29] jointly models user/item representations from reviews. Building on stronger language modeling, RoBERTa [30] provides contextual embeddings that can be precomputed and merged with latent factors. Recent multi-embedding fusion (BERT+RoBERTa) reports consistent gains on review datasets [31]. Recent sequential recommenders leverage transformer-based architectures, such as SASRec [13], BERT4Rec [14], and GRU-based models [32], while Graph Neural Networks (GNNs) capture high-order dependencies on user-item graphs (e.g., LightGCN [33]). In parallel, self-supervised objectives enhance learning from unlabeled signals in graphs and sequences through pretraining via mutual information maximization (S3-Rec) [34]. Although these methods excel in dense sequential regimes, this study focuses on a sparsity-oriented hybridization that unifies latent factors and semantic cues. Accordingly, SEMAR-LF complements the state-of-the-art landscape by unifying semantic regularization and temporal modeling within a probabilistic framework tailored to sparse user-item interactions.

### III. PROPOSED METHOD

The proposed model integrates semantic insights through pre-trained embeddings and enriches the sequence modeling with LSTM to capture the temporal dynamics and address sparsity in the semantic regularization of product reviews.

#### A. Datasets

MovieLens (ML) is the most popular dataset for RSs. The ML datasets are divided into two categories, ML-1M and ML-10M, both having distinct sparseness characteristics, and Table II presents their detailed characteristics [35, 36].

TABLE II. CHARACTERISTICS OF THE RS DATASETS

Dataset	Category			
	Total users	Total items	Total ratings	Density
ML-1M	6,040	3,706	1,000,209	4.47%
ML-10M	69,878	10,677	10,000,054	1.34%
AIV	81,339	18,203	238,352	0.016%

#### B. Evaluation Metrics

The Root Mean Square Error (RMSE) [37, 38] is a standard accuracy metric for rating prediction in RSs, measuring the

average magnitude of error between predicted and actual ratings. RMSE quantifies the difference between these values by penalizing larger errors more heavily due to squaring, making it a reliable indicator of model accuracy. A lower RMSE indicates a better predictive performance. The RMSE is computed as follows, where  $R$  denotes the set of all user-item pairs with observed ratings,  $R_{ij}$  represents the actual rating given by user  $i$  to item  $j$ ,  $\widehat{R}_{ij}$  is the predicted rating generated by the model, and  $|R|$  indicates the total number of observed ratings used for the evaluation.

$$\text{RMSE} = \sqrt{\frac{1}{|R|} \sum_{(i,j) \in R} (R_{ij} - \widehat{R}_{ij})^2} \quad (1)$$

Since this study focuses on rating prediction under sparsity, RMSE and MAE are used as primary metrics because they directly quantify numerical deviations from ground-truth ratings, with RMSE emphasizing significant errors. Since the importance of ranking metrics (Precision@K, Recall@K, NDCG, MAP, and Hit Ratio) for top N recommenders is acknowledged, expanding to these metrics is part of future work to provide a holistic assessment.

#### C. Latent Features in PMF: Unlocking Hidden Patterns in Recommendations

RSs uncover user preferences by factorizing the user-item rating matrix into lower-dimensional representations. SVD pioneered this approach by approximating the interaction matrix with low-rank factors, capturing essential patterns despite sparsity [29]. PMF decomposes the rating matrix into user and item latent spaces and reconstructs the missing ratings using a Gaussian noise model to maximize the likelihood of the observed data. The latent factors are defined as  $U \in R^{D \times N}$  for user features and  $V \in R^{D \times M}$  for item (movie) features.

The PMF model employs a Zero-Mean Spherical Gaussian Prior (ZMSGP) on the user and item latent feature vectors to enhance its probabilistic framework. This prior ensures regularization by constraining the learned latent factors, preventing overfitting and improving generalization, especially in sparse datasets. The ZMSGP is a probabilistic framework where  $U_i$  and  $V_j$  represent the latent feature vectors for user  $i$  and item  $j$ , respectively. The model assumes Gaussian priors  $N(\cdot)$  over these latent variables, with precision parameters  $\lambda_U$  and  $\lambda_V$  regulating the variance of the distributions. The identity matrix ( $I$ ) is used to construct the prior covariance, ensuring regularization and numerical stability during the learning process. ZMSGP is defined as:

$$P(V) = \prod_{j=1}^M cN(V_j | 0, \lambda_V^{-1} I) \quad (2)$$

ZMSGP assumes that the latent feature vectors have a zero mean and are drawn from a multivariate Gaussian distribution with isotropic variance. This assumption simplifies the optimization process while preserving the model's ability to learn meaningful latent representations. The overall objective function for PMF, incorporating ZMSGP, becomes:

$$\mathcal{L}(U, V) = \sum_{(i,j) \in R} (R_{ij} - U_i^T V_j)^2 + \lambda_U |U|_F^2 + \lambda_V |V|_F^2 \quad (3)$$

The second and third terms are regularization terms imposed by ZMSGP to control the complexity of the latent factors. By integrating ZMSGP, the PMF model not only improves its robustness to overfitting but also enhances its capacity to make accurate predictions in sparse recommendation scenarios.

#### D. Deep Semantic and Sequential Integration in a Probabilistic Matrix

The SEMAR-LF model improves the recommendation accuracy by combining semantic embeddings, sequential user dynamics via LSTM, and latent factors through PMF. In the preprocessing stage, reviews are cleaned, tokenized, stop-words are removed, and transformed into GloVe, whereas user-item ratings are normalized and temporally ordered. Figure 1 illustrates the SEMAR-LF architecture integrating semantic enrichment and temporal modeling.

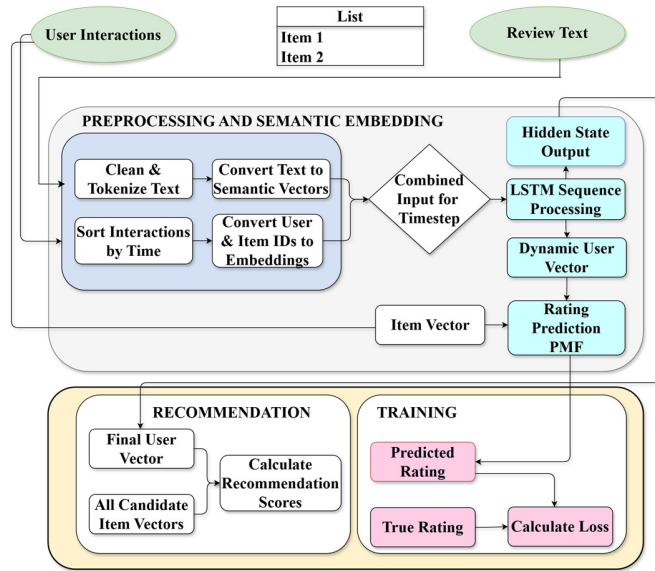


Fig. 1. Schematic of the SEMAR-LF model architecture.

User latent representations  $u_i$  combine latent user factors  $p_{u_i}$  and sequential patterns  $h_{u_i}$  from LSTM:

$$u_i = p_{u_i} + h_{u_i} + \delta_i, \quad \delta_i \sim \mathcal{N}(0, \sigma_U^2 I) \quad (4)$$

Similarly, the item latent representations  $v_j$  integrate PMF factors  $q_{i_j}$ , semantic embeddings  $q_{s_j}$ , and sequential item dynamics:

$$v_j = q_{i_j} + q_{s_j} + \text{LSTM}(W, X_j) + \epsilon_j, \quad \epsilon_j \sim \mathcal{N}(0, \sigma_V^2 I) \quad (5)$$

with semantic embeddings defined as:

$$q_{s_j} = \text{Embedding}_{\text{Glove}}(X_j) \quad (6)$$

The final recommendation prediction  $\widehat{R}_{ij}$  is obtained via the dot product of user and item representations:

$$\widehat{R}_{ij} = (p_{u_i} + h_{u_i})^T (q_{i_j} + q_{s_j} + \text{LSTM}(W, X_j)) \quad (7)$$

#### E. SEMAR-ATT (Attention-Based Semantic Fusion)

The SEMAR-ATT variant that fuses item latent factors with content features (RoBERTa embeddings). A gated-attention head computes:

$$z_j = \sigma(W_1 v_j + W_2 \tilde{e}_j + b) \in (0, 1)^d, \\ v_j^* = z_j \odot v_j + (1 - z_j) \odot \tilde{e}_j \quad (8)$$

where  $\sigma(\cdot)$  is the sigmoid and  $\odot$  denotes element-wise product; LayerNorm on  $e_j$  before  $W_e$  is optional but stabilizes training. This design lets the gate  $z_j$  adaptively weight collaborative ( $v_j$ ) versus semantic ( $\tilde{e}_j$ ) evidence per item, which is beneficial for long-tail sparsity, while preserving a low-latency serving path:  $e_j$  and  $v_j^*$  are computed offline, and online scoring reduces to a single dot-product  $\langle u_i, v_j^* \rangle$ .

As illustrated in Figure 2, this framework incorporates an advanced semantic fusion component designed to enrich the model's contextual understanding. In this submodule, textual data from external sources, such as the Amazon Movie Video datasets, is processed by a RoBERTa model to generate powerful semantic features. Then, an attention mechanism is utilized to integrate these rich precomputed embeddings into the main probabilistic model. This process enables the framework to enhance the item's latent representation ( $v$ ), resulting in more accurate and context-aware rating predictions.

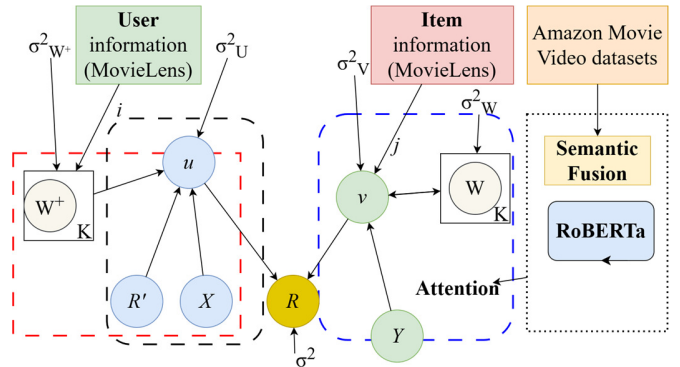


Fig. 2. Hybrid model architecture with semantic fusion.

## IV. RESULTS AND DISCUSSION

The proposed SEMAR-LF algorithm was implemented to evaluate its effectiveness across varying levels of data sparsity and scale. To evaluate the robustness and generalizability of SEMAR-LF, its performance was compared with leading baseline models on two benchmark datasets: ML-1M and ML-10M. Table III presents an RMSE comparison on the ML-1M and ML-10M datasets, providing a detailed summary of the experimental results across varying training splits. On the sparser ML-1M dataset, SEMAR-LF achieved the lowest RMSE in most training splits, notably 0.99280 with only 10% training data, outperforming PMF and ConvMF. Although ConvMF slightly surpassed SEMAR-LF at the 20–80 split,

SEMAR-LF regained superiority as data volume increased, reaching 0.87114 at the 50–50 split—demonstrating its effectiveness in leveraging temporal dynamics and semantic context, even in limited settings. On the larger and denser ML-10M dataset, SEMAR-LF consistently outperformed all baseline models across all splits, with a best RMSE of 0.79020 at the 90–10 configuration. Its hybrid integration of PMF, LSTM, and semantic enrichment allowed it to scale effectively, maintain accuracy, and capture complex patterns in large-scale environments.

TABLE III. RMSE COMPARISON ON ML-1M AND ML-10

Training-split	PMF (ML-1M)	ConvMF (ML-1M)	SEMAR-LF (ML-1M)	PMF (ML-10M)	ConvMF (ML-10M)	SEMAR-LF (ML-10M)
10–90	1.64697	0.99541	0.9928	1.27539	0.93629	0.95506
20–80	1.26577	0.9276	0.93214	1.05233	0.89332	0.89117
30–70	1.11795	0.90507	0.89993	0.96513	0.86621	0.85185
40–60	1.03992	0.88525	0.88458	0.91827	0.84673	0.82737
50–50	0.99064	0.87787	0.87114	0.88834	0.83604	0.81567

Based on the RMSE values in the graph and evaluation tables, SEMAR-LF consistently demonstrates superior performance in most training splits on the ML-1M dataset, as shown in Figure 3. At extreme sparsity (10–90 split), SEMAR-LF achieved the lowest RMSE of 0.99280, slightly outperforming ConvMF. Although ConvMF narrowly surpassed SEMAR-LF in the 20–80 split, SEMAR-LF regained dominance from the 30–70 split onward, recording the best results in the 30–70, 40–60, and 50–50 splits. These results validate the effectiveness of the model in handling varying data densities while accurately capturing temporal dynamics and semantic content.

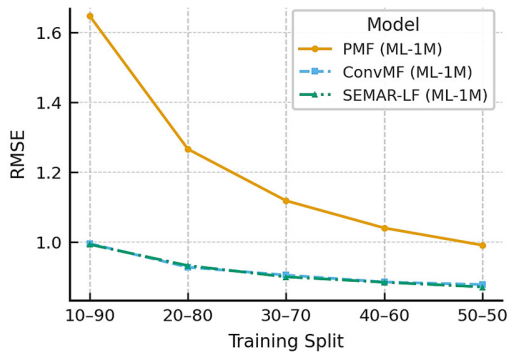


Fig. 3. Experimental results on the ML-1M dataset.

To further validate the effectiveness of SEMAR-LF, a comparative analysis was conducted against several state-of-the-art hybrid collaborative filtering models, including PMF, CTR, CDL, DDL+PMF, and ConvMF. Table IV presents the RMSE scores of all models, including SEMAR-LF, across multiple training splits, highlighting SEMAR-LF’s superior accuracy in each ratio. Meanwhile, Table V provides a more precise depiction of this advantage by quantifying the percentage improvement of SEMAR-LF over the baseline models. This dual presentation illustrates SEMAR-LF’s consistent performance gains and robustness across sparse and dense recommendation scenarios.

TABLE IV. RMSE COMPARISON SEMAR-LF ACROSS TRAINING RATIOS

Ratio (%)	SEMAR-LF	PMF	CTR	CDL	DDL PMF	ConvMF
20%	<b>0.89117</b>	1.43981	1.0266	0.9871	0.90216	0.89231
30%	<b>0.85185</b>	1.06513	0.9593	0.9562	0.8712	0.86273
40%	<b>0.82737</b>	0.97827	0.9376	0.9255	0.8686	0.84512
50%	<b>0.81567</b>	0.96167	0.9212	0.9131	0.8431	0.83513
60%	<b>0.80968</b>	0.96532	0.9088	0.8993	0.8348	0.82683
70%	<b>0.80276</b>	0.95569	0.8934	0.8823	0.8287	0.82157
80%	<b>0.79735</b>	0.95098	0.8912	0.8751	0.8253	0.82081

TABLE V. PERCENTAGE IMPROVEMENT OF SEMAR-LF OVER BASELINE MODELS

Training split	SEMAR-LF RMSE	Improvement vs PMF (%)	vs CTR (%)	vs CDL (%)	vs DDL+PMF (%)	vs ConvMF (%)
20% (80–20)	0.79735	<b>44.62</b>	22.33	19.22	11.62	10.64
30% (70–30)	0.80276	24.63	16.32	16.05	7.86	6.95
40% (60–40)	0.80968	17.23	13.64	12.51	6.78	4.19
50% (50–50)	0.81567	15.18	11.46	10.67	3.25	2.33
60% (40–60)	0.82737	14.29	8.96	8.00	0.89	-0.07

Figure 4 illustrates the percentage improvement achieved by the SEMAR-LF model over various baseline recommendation models in terms of RMSE. The figure illustrates how SEMAR-LF consistently outperforms traditional and hybrid recommendation approaches by incorporating semantic enrichment and temporal modeling.

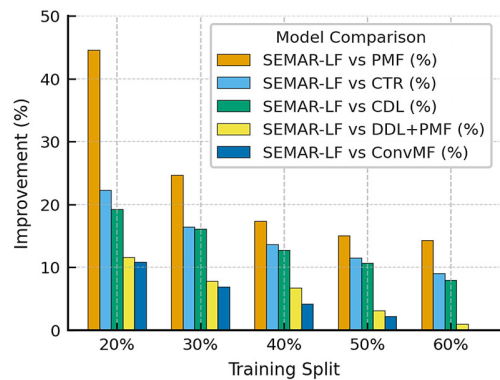


Fig. 4. Percentage improvement of SEMAR-LF.

The results demonstrate that SEMAR-LF consistently outperformed traditional and hybrid baselines, particularly in sparse data settings. For instance, in a 20% training ratio, SEMAR-LF achieved a 44.62% reduction in RMSE compared to PMF and a 22.33% improvement over CTR, while also outperforming CDL and DDL+PMF by 19.22% and 11.62%, respectively. The model also surpassed ConvMF by 10.64%, underscoring the significant benefit of incorporating semantic regularization and temporal modeling.

Integrating semantic regularization, latent factors, and sequential modeling enhances recommendation accuracy by aligning hidden item features with semantic review embeddings, thereby improving the accuracy of recommendations. These embeddings are dynamically weighted by paying attention to pre-existing, trained embeddings. The efficacy of the proposed SEMAR-LF framework is demonstrated by its substantial improvements in accuracy, context-awareness, and resilience to sparsity. These gains were validated using standard benchmarks, such as ML-1M, ML-10M. Notably, the SEMAR-LF framework maintains scalability across datasets, which is a crucial attribute for modern data management and analysis.

To validate content fusion, a complementary SEMAR-ATT ablation on the merged ML set (ML-1M+ML-10 M) was performed using 768-dim simulated content features with an 80–20 split. Table VI summarizes the RMSE/MAE for the rating prediction. Relative to the global-mean baseline (RMSE 1.0662; MAE 0.8640), SEMAR-ATT attains RMSE 0.8565 and MAE 0.6655, yielding absolute reductions of 0.2097 in RMSE.

TABLE VI. RATING PREDICTION RESULTS FOR SEMAR-ATT

Model	RMSE	MAE	Improv. % (RMSE)	Improv. % (MAE)
Baseline (Global Mean)	1.0662	0.8640	-	-
PMF + ATT + RoBERTa	0.8565	0.6655	19.7%	23.0%

SEMAR-ATT improves over a global-mean baseline by ~19.7% RMSE and ~23% MAE. These gains indicate that injecting semantic-like signals yields consistent benefits even with simulated features. The ablation complements the SEMAR-LF results, motivating richer attention-based fusion once real RoBERTa embeddings are integrated.

Semantic-enriched latent factor models significantly enhance RSs by embedding contextual information from product reviews and textual features into latent representations, thereby enriching the user–item interaction space. This enrichment enables the model to capture better-hidden preferences and item characteristics, particularly valuable in sparse scenarios with limited historical data. By aligning latent factors with semantic signals, the accuracy of recommendations and personalization is substantially improved compared to models that rely solely on numerical ratings.

However, its practical deployment hinges on overcoming challenges such as increased computational complexity and a strong dependence on high-quality textual data, such as knowledge distillation to create a more lightweight version of SEMAR-LF. Future work focusing on model optimization and more efficient semantic architectures will be crucial for translating SEMAR-LF's powerful performance into scalable, real-time e-commerce solutions. This approach efficiently addresses sparse data issues by leveraging computational capabilities and high-quality textual information, thereby establishing a new standard for accurate and scalable recommendations in e-commerce. In addition, it provides a

foundation for future developments in multimodal and transformer-based systems.

Textual product data is a high-value signal for personalization. Injecting these text-based semantics into the recommendation pipeline enhances item relevance under sparsity, thereby increasing satisfaction and loyalty by aligning results with users' expressed preferences. In practice, semantic enrichment of reviews enables intent-aware experiences—e.g., semantic search, tailored cross-sell/upsell, and targeted promotions—without relying solely on dense interaction histories.

## V. CONCLUSION

This study presented SEMAR-LF, a hybrid recommendation model that effectively integrates PMF, LSTM networks, and semantic regularization via pre-trained word embeddings. The model addresses common challenges in recommender systems, such as data sparsity, lack of contextual understanding, and temporal dynamics. Experimental evaluations on two benchmark datasets—ML-1M and ML-10M—demonstrate that SEMAR-LF consistently outperforms several state-of-the-art baseline models, including PMF, ConvMF, and CTR-based methods. SEMAR-LF achieved the lowest RMSE values across most training splits, indicating its robustness and adaptability in sparse and large-scale environments. Fusing latent factors, sequential user behavior, and semantic information significantly enhances prediction accuracy and personalization capability. As a complementary pilot, a lightweight SEMAR-ATT variant (PMF+RoBERTa-based content fusion) validates the effectiveness of semantic fusion even with simulated features. In summary, SEMAR-LF delivers a deployment-friendly probabilistic hybrid for sparse environments, and SEMAR-ATT corroborates the benefit of lightweight attention-based semantic fusion. Future work will extend this family with fusion mechanisms, RL-driven, and multimodal enrichment.

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