WUsim: Enhancing Memory-Based Collaborative Filtering with Wasserstein Similarity and User Profile Correlation

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ABSTRACT

The performance of Collaborative Filtering (CF), which is commonly used in recommendation systems, often deteriorates under data sparsity and in the presence of cold-start users. To address this issue, this study proposes Wasserstein-User Profile Correlation Similarity (WUsim), a hybrid similarity model that combines Wasserstein Distance to capture similarity in rating distributions, with User Profile Correlation (UPC) to model behavioral proximity and user characteristics. This integration enables accurate similarity calculations even when co-rated items are limited. Evaluation on MovieLens-100K and MovieLens-1M using a random split (80:20) and a cold-start protocol demonstrates consistent improvements in rating prediction accuracy, measured by Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). On MovieLens-100K, WUsim achieves a best RMSE of 1.083, while on MovieLens-1M the best RMSE is 1.025, and paired statistical significance testing ($\alpha = 0.05$) confirmed that the observed improvements are statistically significant. Overall, these results indicate that the proposed hybrid similarity approach improves the robustness of CF against sparsity and cold-start, and generates more stable, informative, and efficient recommendations across various data scales.

Keywords-recommendation systems; collaborative filtering; hybrid similarity; Wasserstein distance; user profile correlation; sparse data; cold-start

I. INTRODUCTION

Recommendation systems have become an essential component across a wide range of digital platforms, from e-commerce and streaming services to online education and social media [1], with the main goal of improving user experience by presenting personalized recommendations based on user interaction history and preferences [2]. Among the various existing approaches, Collaborative Filtering (CF) remains the most widely used method due to its simple concept, competitive predictive performance, and its ability to leverage similarity patterns between users and items [3]. Nevertheless, memory-based CF still faces two classic challenges: data sparsity and scalability.

In many real-world datasets, the user-item matrix is highly sparse, limiting the reliability of similarity estimation [4]. Furthermore, the sheer growth of users and items further increases the computational burden on methodologies, like K-Nearest Neighbors (KNN), that are used for the search process and the storage of large similarity matrices [5].

Several approaches have been proposed to mitigate these limitations, including Matrix Factorization (MF) [6], statistical methods and alternative similarity measures, hybrid normalization techniques, and deep learning-based models [7]. MF achieves improved accuracy by projecting user preferences into a low-dimensional latent space, whereas neural approaches can extract nonlinear relationships [8]. However, both categories require large amounts of data, are computationally intensive, and are often inadequate in cold-start scenarios [9]. Hybrid recommendation models have also been explored using auxiliary features or advanced learning techniques to improve recommendation accuracy under sparse data conditions [10].

Recent developments indicate increased attention to optimal transport, particularly the Wasserstein distance, for modeling distributional similarity in recommendation systems [11]. Wasserstein provides a more stable distance measure against limited rating conditions, making it effective for addressing sparsity and cold start users [12]. On the other hand, profile-based approaches such as User Profile Correlation (UPC) highlight the importance of leveraging demographic and user behavior information to improve recommendation quality when rating data is limited [13]. Several other hybrid studies, for example, CF SVD++, CF deep learning, and embedding models, have demonstrated the benefits of feature fusion [14]. However, most do not simultaneously integrate distributional similarity (Wasserstein) and profile similarity (UPC) within a single efficient CF framework. Additionally, prior work has predominantly emphasized item-item relationships or relied on limited auxiliary features, restricting effectiveness in user cold-start scenarios [15, 16].

To the best of our knowledge, no existing method jointly integrates both distributional similarity and profile similarity under global similarity computation in an efficient CF setting. Based on this identified gap, this study introduces Wasserstein-User Profile Correlation Similarity (WUsim), a hybrid similarity model designed for user-based CF [17]. This framework incorporates distributional similarity derived from the Wasserstein distance together with user-profile-based similarity modeled through UPC [18]. In addition, local similarity based on Cosine and Jaccard measures is employed to preserve direct interaction signals when co-rated items are available. These similarity components are integrated through a structured local-global fusion mechanism within a stable and efficient KNN-based CF framework, enabling reliable similarity estimation under sparse and cold-start conditions [19]. The proposed model is evaluated on two widely used benchmark datasets, MovieLens-100K and MovieLens-1M, using two experimental protocols: a random split to assess overall recommendation performance and a cold-start user protocol to simulate new-user scenarios [20].

To position this work within the CF landscape, Table I presents a structured comparison of representative similarity models across five aspects: reliance on co-rated items, capability to capture cross-item relations, modeling of rating distributions, utilization of user-profile information, and effectiveness in cold-start scenarios. The comparison shows that traditional similarity measures, such as Cosine and Jaccard, tend to degrade substantially under sparse conditions because they rely heavily on the presence of co-rated items [21]. Profile-based approaches like UPC achieve improvements by incorporating auxiliary user information, yet they still overlook the distributional characteristics of user ratings, limiting their flexibility [22]. Meanwhile, hybrid methods such as Wasserstein Collaborative Filtering (WCF) incorporate distributional information but do not jointly exploit both distributional similarity and user-profile similarity, leaving an important methodological gap [23].

In contrast, the proposed WUsim introduces a unified hybrid similarity model that integrates rating distributions, user profiles, and co-rating information simultaneously [24]. By combining these three complementary sources, WUsim produces more stable and adaptive similarity estimates, enabling improved robustness in sparse and cold-start environments compared with previous CF approaches [25].

TABLE I. COMPARISON OF SIMILARITY METHODS

Model Similarity	**Approach Type**	**Co-Rated Items**	**Cross-item Relations**	**Rating Distribution Modeling (Wasserstein)**	**User Profile**	**Cold Start Capability**
Cosine [5]	Traditional	☑	☒	☒	☒	Low
WCF [12]	Hybrid (item-oriented)	☑	☑	☑	☑	Medium
UPC [13]	Profile-based	☒	☒	☒	☒	Medium
Jaccard [26]	Traditional	☑	☒	☒	☒	Low
WU (Proposed)	Hybrid (User and distribution-oriented)	☑	☑	☑	☑	High

II. RESEARCH METHODOLOGY

Figure 1 presents the overall workflow of the proposed WUsim. The initial stage includes data preparation, encompassing user demographic information, genre metadata, and rating data. All similarity calculations are performed on a user-based path. The next stage constructs global similarity by integrating Wasserstein distance and UPC, as well as local similarity using Cosine and Jaccard measures. The final similarity value for prediction is obtained by combining these components through a hybrid similarity mechanism [27].

The Wasserstein distance quantifies distributional similarity between users based on probabilistic rating patterns, while UPC assesses behavioral proximity using genre preferences and demographic attributes. By integrating these two global perspectives, WUsim maintains sensitivity to rating distribution structure, as in WCF, while enabling similarity estimation even when users have no co-rated items. The hybrid similarity fusion mechanism then combines local and global components to produce a final similarity score that serves as the basis for rating prediction.

Unlike item-based models like WCF, WUsim does not implement an item-based CF strategy, although it utilizes item information such as genre and other movie metadata. Instead, item information is used only to construct user profiles for the UPC component and to calculate local similarity, which requires co-rated items. Therefore, the entire similarity calculation process is entirely on the user-based path, eliminating the need for item-based components in the methodological structure.

By leveraging the local-global similarity structure and replacing the two global-similarity dimensions with more informative components, this proposed model can be viewed as an extension of the WCF approach. On the local similarity path, WUsim still maintains the CF principle based on shared ratings, using Cosine and Jaccard as representations of directly observable rating behavior. Meanwhile, the extension is made along the global similarity path by integrating two new similarity components that provide a deeper understanding of rating distributions and user profile characteristics [28].

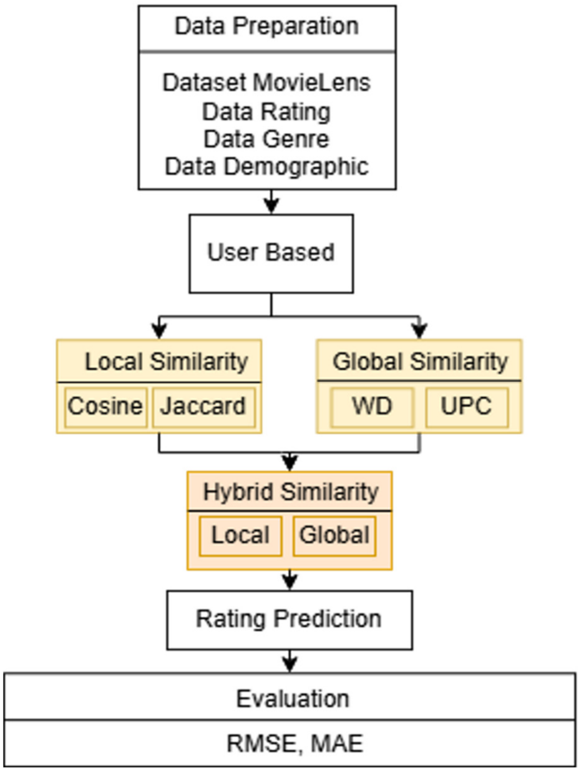

Fig. 1. Research methodology.

A. Data Preparation

This research uses two benchmark datasets, MovieLens-100K and MovieLens-1M, which are publicly available from the GroupLens Research Group [29]. The datasets were originally introduced and described in [30] and have been widely used for evaluating CF models due to their consistent annotations and stable rating structures [31]. The use of two datasets with different sizes allows testing the performance of WUsim in terms of accuracy, sparsity resistance, and scalability in large-scale data scenarios.

The MovieLens-100K dataset contains 100,000 ratings on 1,682 movies from 943 users, with ratings on a 1-5 scale. The corresponding user-item matrix has a density of approximately 6.3%, indicating high sparsity and making it suitable for evaluating models designed to handle data scarcity [32]. On the other hand, the MovieLens-1M dataset contains 1,000,209 ratings on 3,952 movies from 6,040 users.

In addition to user-id, item-id, and rating, the dataset provides demographic metadata such as age, gender, and occupation. This demographic information is used to construct the UPC component for global similarity. Moreover, movie genre metadata is also incorporated to enrich user profile representation and improve adaptability under cold-start conditions.

Table II summarizes the key characteristics of both datasets, including size, structure, and sparsity. Both MovieLens-100K and MovieLens-1M have sparsity levels above 93%, making them appropriate benchmarks for evaluating models designed for sparse data and limited user interactions. The differences in size levels between datasets also support a more in-depth evaluation of the stability and generalizability of the WUsim model.

TABLE II. DATASET DESCRIPTIONS

Dataset	User	Items	Rating	Rating Scale	Sparsity
MovieLens-100K	943	1,682	100,000	[1…5]	93.70%
MovieLens-1M	6,040	3,952	1,000,209	[1…5]	95.75%

B. Preprocessing

The initial preprocessing step aligns the data structures across the two MovieLens datasets by filtering out invalid entries, remapping user and item indices, and normalizing rating formats. To maintain consistency in sparsity levels, each rating is then represented in a user-item matrix with a fixed scale of 1-5. Additionally, all users and items with at least one relevant interaction are retained in the dataset.

In the UPC component, user demographic data, such as age, gender, and occupation, are transformed using label encoding and grouped into computational categories, allowing stable vector representations for global similarity calculation. Moreover, to match film genre metadata with user behavior profiles, genre information is converted using multi-hot encoding, which captures variation in users' genre preferences by aggregating each user's individual film consumption patterns.

Then, the user rating distributions for Wasserstein distributional similarity computation are constructed. Each user is represented as a probability distribution derived from a rating histogram, which enables optimal transport computation to quantify similarity between rating distribution shapes, even with minimal overlap in rated items [33].

C. Local Similarity

The local similarity component initiates the assessment of user proximity by analysing rating patterns across co-rated items. In this study, local similarity is computed using two widely adopted similarity measures: Cosine similarity and Jaccard similarity. Cosine similarity evaluates the directional closeness between two users' rating vectors over the set of commonly rated items, while Jaccard similarity measures the proportion of shared rated items relative to the total number of items rated by either user, making it particularly suitable for sparse interaction scenarios.

Let I_{uv} denote the set of items co-rated by users u and v. The Cosine similarity between users u and v is defined in (1), and the Jaccard similarity is given in (2), where I_u and I_v represent the sets of items rated by users u and v, respectively. The final local similarity is obtained by combining both measures through multiplication (3):

$$\text{Cosine}(u,v) = \frac{\sum_{i\in I_{uv}} r_{u,i}\, r_{v,i}}{\sqrt{\sum_{i\in I_{uv}} r_{u,i}^2}\ \sqrt{\sum_{i\in I_{uv}} r_{v,i}^2}} \qquad (1)$$

$$\text{Jaccard}(u,v) = \frac{|I_{uv}|}{|I_u \cup I_v|} \qquad (2)$$

$$S_{\text{loc}}(u,v) = \text{Cosine}(u,v) \cdot \text{Jaccard}(u,v) \qquad (3)$$

where $r_{u,i}$ and $r_{v,i}$ represent the ratings given by users u and v to item i. As a result, local similarity in WUsim is consistent with the fundamental WCF principle that direct interaction plays a significant role in forming similarities; however, the calculation formulation has been streamlined and optimised to better suit the sparse data conditions of this study.

D. Global Similarity

The global similarity component captures information not available from the local similarity component, namely, rating distribution structure and similarity based on user behavior profile.

First, the first-order Wasserstein distance between users quantifies dissimilarity between their rating distributions within the optimal transport framework [34]. Then, the formula in (4) transforms this distance into a similarity score using a damped exponential function, where parameter τ controls sensitivity to distributional differences. This formulation assigns high similarity options to users with similar rating distributions, even without overlapping rated items.

Next, by integrating rating inclination similarity S_r and profile-based similarity S_b derived from demographic and genre preferences, this study adopts a user behaviour viewpoint through the UPC, as defined in (5). UPC is modeled as a weighted combination $S_{UPC} = \alpha S_r + \beta S_b$ with $\alpha + \beta = 1$. The weights α and β are computed in a data-driven manner based on the relative variability of the two profile components. In the last step, the two global similarity components, Wasserstein similarity and UPC, are fused geometrically using (6):

$$S_{\text{WD}}(u,v) = exp\left(-\frac{W_1(u,v)}{\tau}\right) \qquad (4)$$

$$S_{\text{UPC}}(u,v) = \alpha\, S_r(u,v) + \beta\, S_b(u,v) \qquad (5)$$

$$S_{\text{global}}(u,v) = S_{\text{WD}}(u,v)^{\lambda}\ S_{\text{UPC-norm}}(u,v)^{1-\lambda} \qquad (6)$$

To obtain the final similarity, WUsim combines both local and global similarity components. Let $S_{\text{loc}}(u,v)$ denote the local similarity derived from co-rated items (Cosine and Jaccard), and $S_{\text{global}}(u,v)$ represent the global similarity produced by the geometric fusion of Wasserstein and UPC. The final WUsim similarity is defined as:

$$S_{\text{WU}}(u,v) = S_{\text{loc}}(u,v) + S_{\text{global}}(u,v) \qquad (7)$$

This additive fusion formulation enables WUsim to leverage complementary information: local similarity captures micro-level rating agreement from co-rated items, while global similarity incorporates macro-level distributional and profile attributes that remain informative even when co-rated items are scarce.

The parameters α, β, λ, and τ used in the proposed WUsim model are not learned through an optimization or training process; instead, they are fixed across all experiments and selected heuristically to balance the contributions of local and global similarity components. Specifically, α and β regulate the relative influence of different user profile attributes in the UPC component, while λ controls the strength of the global similarity fusion and τ governs the smoothing behavior in the Wasserstein-based similarity computation. Keeping these parameters fixed ensures computational efficiency, reproducibility, and fair comparison across different datasets and evaluation protocols.

E. Rating Prediction

The final stage of WUsim is the rating prediction process, where the model estimates the rating a user may assign to items they have not yet rated. This stage employs a memory-based CF approach using a weighted KNN scheme, ensuring that only the most similar users contribute to the prediction. Similarity weights are derived from the hybrid WUsim measure, which combines global and local similarity components. As a result, neighbours with higher similarity exert a more substantial influence on the predicted value.

Importantly, the integration of Wasserstein distance and user-profile correlation enables similarity computation even when few or no co-rated items exist, making WUsim resilient to sparse and cold-start conditions.

It is important to note that completely new users with zero interactions cannot be simulated using the MovieLens datasets because such scenarios require additional side information or cross-domain data that are not available in these datasets. Therefore, this study focuses on users with limited interactions rather than zero-interaction users.

III. RESULTS AND DISCUSSION

A. Experimental Setup

Experiments were conducted on a Windows 10 Pro 64-bit system equipped with an Intel Core i5-2557M 1.70 GHz processor and 10 GB Random Access Memory (RAM). The WUsim model was fully implemented in Python 3.13.3 using scientific libraries such as NumPy, Pandas, SciPy, and scikit learn, while Sublime Text served as the development environment. This hardware and software configuration is sufficient for executing Wasserstein and UPC-based similarity computations, including large-scale matrix operations.

Performance evaluation used the MovieLens-100K and MovieLens-1M datasets across two testing scenarios: i) an 80:20 random split to assess overall accuracy, and ii) a cold-start protocol in which 20% of users were treated as new users with only their first five interactions retained in training, and the subsequent twenty interactions are used for testing. To simulate realistic conditions, the interactions of warm users are further sparsified by randomly dropping 80% of ratings. The entire process is repeated five times with different subsets of cold users, and the average performance is reported to ensure robustness.

All stages, including preprocessing, local similarity computation, global similarity calculation, hybrid fusion, and weighted KNN prediction, were executed within the same computational environment.

The experiment involved evaluating the WUsim model alongside several baseline techniques representing major similarity approaches in recommender systems, as summarized in Table I. All baseline methods were assessed using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for rating prediction accuracy. Table III lists all the key parameter values that were used, while Table IV outlines the cold-start protocol, detailing the proportion of cold-start users, the number of retained interactions, the sparsity level among warm users, and the number of evaluation rounds.

TABLE III. WU SIMILARITY MODEL PARAMETER

Component	Parameter	Description	Value
Wasserstein Distance	τ	Smoothing factor for rating distribution	0.8
	η_{wass}	Item popularity regularization	0.1
UPC	α	Similarity weight based on rating pattern S_r	Data-driven weighting (computed from profile correlation)
	β	Behavior/genre-based similarity weights S_b	Data-driven weighting (computed from profile correlation)
	(Constraint)	Weight normalization	$\alpha + \beta = 1$
Fusion (Global Similarity)	λ	Bobot geometric fusion (Wasserstein-UPC)	0.3
	φ_{add}	Additive fusion weight (Local-Global)	0.3
KNN Prediction	K	List of tested neighbor values	{10…100}
Rating Prediction	Rating Range	Rating value limit	[1…5]

TABLE IV. PARAMETERS OF COLD-START PROTOCOL

Component	Parameter	Value
Cold user fraction	cold_frac	20%
Retained interactions	per_cold_train	5
Test interactions	per_cold_test	20
Warm user sparsity	sparsify_drop	0.8
Repeats	n_subsets	5

B. *Performance Analysis*

The performance results when using the MovieLens-100K dataset indicate that WUsim consistently outperforms all baseline methods across every K value. As shown in Figure 2 and Table V, WUsim achieves the lowest MAE of 0.847 at K = 30, improving upon Cosine (0.883), Jaccard (0.886), and WCF (0.903). Similarly, its RMSE of 1.083 is the lowest among all methods. A similar trend is observed on the MovieLens-1M dataset. As presented in Figure 3 and Table V, WUsim records the lowest MAE (0.799 at K = 40) and RMSE (1.025), surpassing Cosine, Jaccard, WCF, and UPC. These results indicate that the integration of Wasserstein similarity and UPC contributes positively to prediction accuracy across different dataset scales.

In addition to the performance metrics, statistical significance testing (paired t-test) was conducted to validate the robustness of the observed improvements. As reported in Table VI, WUsim demonstrates statistically significant improvements over all baseline methods (Cosine, Jaccard, WCF, and UPC) using a paired t-test, with p-values < 0.001 at α = 0.05. This outcome is consistent with the nature of the evaluation metrics, as MAE and RMSE are continuous error measures, making them well-suited for mean-based paired comparisons. These findings confirm that the observed improvements are not only consistent but also statistically robust.

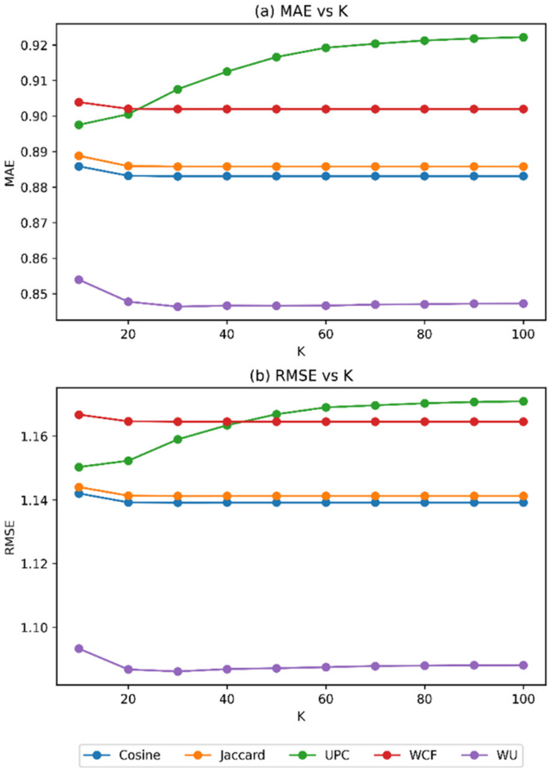

Fig. 2. Performance of five methods with different *K* in term of MAE and RMSE on the MovieLens-100K dataset.

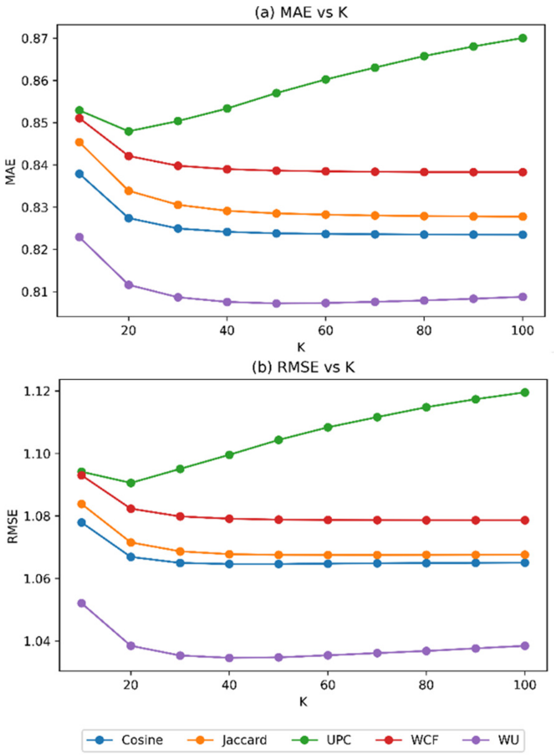

Fig. 3. Performance of five methods with different *K* in terms of MAE and RMSE on the MovieLens-1M dataset.

From a methodological perspective, these improvements can be interpreted intuitively. The Wasserstein distance captures distributional similarity between users, making it less sensitive to sparsity in co-rated items, while UPC provides complementary structural information in the user attribute space. By combining these two components, WUsim constrains similarity estimation across two orthogonal spaces, resulting in lower-variance and more reliable similarity estimates, particularly for sparse users.

TABLE V. BEST PREDICTION ACCURACY

Method	**MovieLens 100K**			**MovieLens 1M**		
	Best K	***Best MAE***	***Best RMSE***	***Best K***	***Best MAE***	***Best RMSE***
Cosine	20	0.883	1.139	60	0.814	1.055
Jaccard	20	0.886	1.141	80	0.818	1.056
WCF	10	0.903	1.166	20	0.838	1.081
UPC	10	0.897	1.151	100	0.826	1.063
WUsim (Proposed)	30	0.847	1.083	40	0.799	1.025

TABLE VI. STATISTICAL SIGNIFICANCE TEST RESULTS (MAE)

Method	**Test**	**P-Value**	**Significant (α=0.05)**
WU vs Cosine	Paired t-test	< 0.001	Yes
WU vs Jaccard	Paired t-test	< 0.001	Yes
WU vs WCF	Paired t-test	< 0.001	Yes
WU vs UPC	Paired t-test	< 0.001	Yes

Further insight is provided by the ablation study presented in Table VII, which evaluates the contribution of each component in WUsim. Among the ablated variants, removing the UPC component results in smaller performance degradation than removing the Wasserstein component, suggesting that distributional similarity contributes more strongly to rating prediction accuracy. However, the complete WUsim model still achieves the best overall performance, confirming that the integration of distributional and profile-based similarity yields more robust predictions under sparse conditions.

TABLE VII. ABLATION STUDY

Similarity	**MovieLens-100K**			**MovieLens-1M**		
	Best K	***Best MAE***	***Best RMSE***	***Best K***	***Best MAE***	***Best RMSE***
WUsim (Without Global)	30	0.885	1.141	100	0.830	1.076
WUsim (Without Wasserstein)	60	0.848	1.090	100	0.820	1.063
WUsim (Without UPC)	30	0.844	1.084	100	0.811	1.049

IV. CONCLUSION

This study proposes Wasserstein-User Profile Correlation Similarity (WUsim), a hybrid similarity model that integrates Wasserstein-based distributional similarity and User Profile Correlation (UPC) to improve memory-based Collaborative Filtering (CF) under sparse and cold-start conditions. Unlike traditional similarity measures that rely exclusively on co-rated items, WUsim constructs global similarity from rating distributions and user attributes, enabling more informative similarity estimation when user interactions are limited.

Experiments on the MovieLens-100K and MovieLens-1M datasets demonstrate that WUsim achieves consistent improvements in rating prediction metrics, based on the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) metrics, compared to representative similarity-based CF baselines. Combined with paired statistical significance testing, these findings indicate that hybrid distributional-profile similarity provides a more robust mechanism for addressing sparsity and partial cold-start scenarios.

Despite these promising results, WUsim still exhibits limitations. The current implementation relies on simplified rating histograms and demographic attributes, which may not fully capture behavioral complexity in domains with incomplete profile information. Additionally, extreme cold-start cases (zero-interaction users) and scalability at web-scale remain open challenges.

Future work will focus on extending the similarity model toward multidimensional or Sinkhorn-based optimal transport, integrating contextual or embedding-based features, and evaluating Top-N recommendation relevance in cross-domain and real-time scenarios.

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