HANOI UNIVERSITY OF SCIENCE AND TECHNOLOGY

SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING

PROJECT I

TITLE: Recommender System for Personalized Poem Suggestions

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ABSTRACT

In an age of content overload, recommending personalized poems poses unique challenges due to sparse user interaction and the subjective nature of preferences. This project proposes a hybrid recommender system that combines both implicit feedback (likes) and explicit feedback (ratings) to improve recommendation accuracy. Using the LightFM model with a WARP loss function, we preprocess and merge data from three sources: likes.csv, ratings.csv, and poems.csv, creating a unified interaction matrix. The model was trained and evaluated on this dataset, with 80/20 train-test splits repeated across multiple runs. Results show consistent improvements in precision@k and recall@k metrics, indicating the system's capability to deliver meaningful and relevant poem recommendations based on both user behavior and preferences.

CHAPTER 1: INTRODUCTION

In the digital era, users are constantly overwhelmed by the abundance of content available online, from news articles to music and literature. Among these, poetry remains a niche yet culturally significant form of expression that lacks personalized recommendation systems compared to mainstream media like movies or products. Unlike e-commerce or streaming platforms, where recommendation engines are widely used, poetry platforms often rely on static categorizations or manual browsing. This gap highlights the need for intelligent systems that can understand and suggest poems aligned with individual user preferences.

Recommending poems presents several challenges. First, user interaction data is typically sparse, as users may read without rating or liking content. Second, poetry preferences are highly subjective, influenced by personal taste, emotional state, or cultural background. From a practical standpoint, an effective poem recommender system could enhance digital libraries, educational tools, and poetry-sharing platforms by boosting engagement and discovery. However, achieving relevant recommendations in such a context requires models that can deal with sparse data and subtle user signals.

Current approaches to recommender systems largely fall into three categories: content-based filtering, collaborative filtering, and hybrid models. Content-based methods often struggle with limited metadata in poems, while collaborative filtering suffers from the cold-start problem and data sparsity. Some platforms have begun exploring hybrid models to balance these limitations, but few are tailored for domains like poetry, where emotional and implicit cues are critical. Additionally, most systems rely heavily on explicit ratings, which are often unavailable or inconsistent in poetry contexts.

To address these challenges, our project proposes a hybrid recommender system utilizing the LightFM model with a WARP (Weighted Approximate-Rank Pairwise) loss function. This method effectively combines implicit (likes) and explicit (ratings) feedback to generate personalized suggestions. By merging and processing user interactions from multiple sources, we create a more comprehensive dataset and leverage LightFM’s ability to model both collaborative and content-based signals. The novelty lies not only in applying LightFM to poetry—a relatively unexplored domain—but also in demonstrating its effectiveness with limited, real-world data, offering a scalable solution for personalized literary experiences.

CHAPTER 2: RELATED WORKS

Recommender systems have been extensively studied and deployed across various domains such as e-commerce (e.g., Amazon), entertainment (e.g., Netflix, Spotify), and social media platforms. Traditional collaborative filtering techniques, including matrix factorization and nearest-neighbor methods, have shown effectiveness when sufficient user-item interactions are available. This chapter reviews relevant research and methodologies that inform our approach.

2.1 Metadata Embeddings for User and Item Cold-start Recommendations

The study by Maciej Kula (2015) [1] introduced the LightFM model, a hybrid approach that combines collaborative filtering with metadata embeddings to effectively address cold-start problems and data sparsity. This model has since been widely adopted in recommendation systems for products and movies, showcasing its versatility and robustness.

2.2 Hybrid Recommender Systems: A Systematic Literature Review

The systematic literature review by Erion Çano & Maurizio Morisio (2019) [2] categorized and analyzed various hybrid recommender systems. Their findings highlight that combining content-based and collaborative methods significantly improves recommendation quality, especially in sparse and noisy environments.

2.3 A Poetry Recommender System for Digital Literary Mediation

This study [3] explored the unique challenges of recommending poetry in digital settings. The study emphasized user engagement, emotional context, and the limitations of traditional tag-based filtering when applied to literary content. This aligns closely with our project's goals, which seek to enhance poem discovery through more personalized, data-driven approaches.

2.4 Existing Approaches and Challenges

Recommender systems traditionally use either collaborative filtering (CF) or content-based filtering (CBF). CF relies on user-item interaction data but struggles with cold-start and sparsity, especially in domains like poetry where explicit feedback is rare. CBF depends on item metadata, which is often limited or unstructured in literary content.

Hybrid models, such as LightFM, combine CF and CBF to overcome these limitations by integrating both implicit and explicit feedback. While effective in many domains, these models still face challenges in poetry recommendation, where user preferences are highly subjective and signals are often weak or implicit.

Most existing systems are built for large-scale platforms (e.g., e-commerce, streaming) and are rarely adapted to niche, emotionally-driven domains. This creates a need for systems that can operate under sparse data conditions while still capturing individual user tastes—precisely what this project addresses.

CHAPTER 3: METHODOLOGY

3.1 Preprocessing data

Three separate datasets were used: likes.csv (implicit feedback), ratings.csv (explicit feedback from 1 to 5), and poems.csv (poem metadata). The likes and ratings files contain user interactions, where each user may have liked or rated multiple poems. These interactions were stored in list format, which were then processed using Python's ast.literal_eval() and exploded into individual rows. Each interaction was assigned a value: 1 for likes, and a score between 1–5 for ratings. A unified dataset was formed by merging both sources, with consistent column names and interaction labels.

The preprocessing phase involved transforming raw interaction data from the likes.csv and ratings.csv files into a structured format suitable for model training.

3.1.1 Parsing Interaction List

Both likes.csv and ratings.csv contain user interactions stored as Python-style list strings. These were safely parsed using ast.literal_eval() to convert them into usable Python list objects. This step was essential for expanding the data into individual (user, poem) interactions.

3.1.2 Exploding Data

Each user's interaction list was "exploded" into separate rows using Pandas. For likes.csv, each liked poem was assigned a fixed value of 1 and labeled as implicit feedback. For ratings.csv, each poem-rating pair was extracted, preserving the user ID, poem ID, and rating value (from 1 to 5), and marked as explicit feedback.

3.1.3 Unifying Interaction Logs

The resulting dataframes from likes and ratings were merged into a single dataset with standardized column names: user, poem_id, value, and source. This combined table reflects all available interactions and allows the model to learn from both implicit and explicit signals.

3.1.4 Encoding Users and Items

Since LightFM requires numerical indices for users and items, all user and poem IDs were transformed into integer values using LabelEncoder. This ensured that the interaction matrix was properly structured and indexed.

3.1.5 Creating the Sparse Matrix

A sparse matrix in COO (Coordinate) format was constructed using scipy.sparse.coo_matrix, where rows represent users, columns represent poems, and values represent the interaction strength (e.g., rating score or implicit like). This matrix was the final input for model training.

3.2 Interaction Matrix Construction

To build a recommender model, both users and poems were encoded into numerical IDs using LabelEncoder. A sparse interaction matrix was created using scipy.sparse.coo_matrix, which maps users to poems with the corresponding interaction value. This matrix served as the input to the recommendation algorithm.

3.3 Model Training with LightFM

3.3.1 Proposed framework

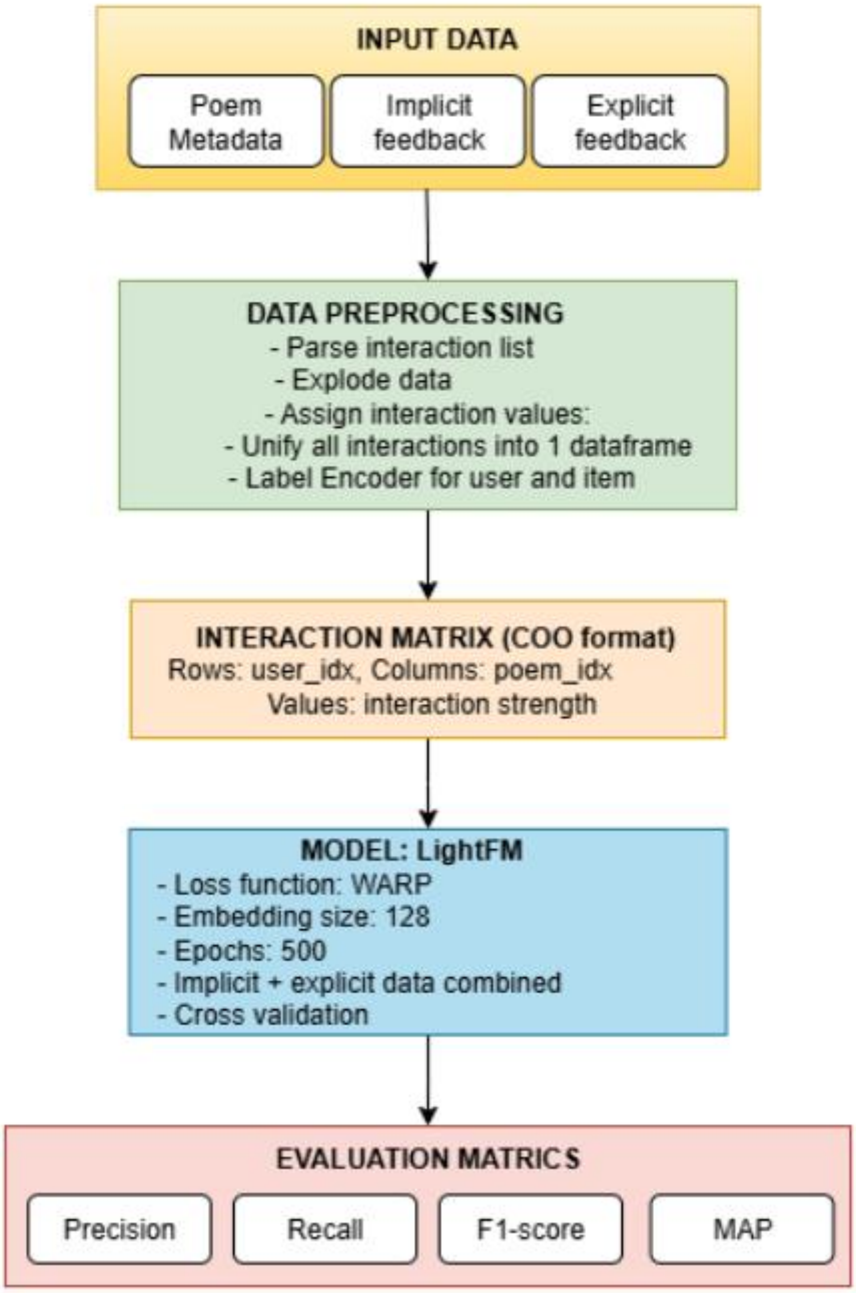


Figure 3.3.1 *Overall Framework*

3.3.2 Overview of LightFM

LightFM is a hybrid recommendation algorithm developed to handle both implicit and explicit feedback, while integrating user and item metadata when available. It was introduced by Maciej Kula (2015) [1] to overcome common challenges in recommender systems, such as cold-start problems and data sparsity.

To describe the model formally, let U be the set of users, I be the set of items, F^U be the set of user features, and F^I the set of item features. Each user interacts with a number of items, either in a favourable way (a positive interaction), or in an unfavourable way (a negative interaction). The set of all user-item interaction pairs $(u, i) \in U \times I$ is the union of both positive S^+ and negative interactions S^{-}.

Users and items are fully described by their features. Each user u is described by a set of features $fu \subset F^U$. The same holds for each item i whose features are given by $fi \subset F^I$. The features are known in advance and represent user and item metadata.

The model is parameterised in terms of d-dimensional user and item feature embeddings e_f^U and e_f^I for each feature f. Each feature is also described by a scalar bias term (b_f^U for user and b_f^I for item features).

The latent representation of user u is given by the sum of its features' latent vectors:

$$q_u = \sum_{j \in f_u} e_j^U$$

The same holds for item i:

$$p_i = \sum_{j \in f_i} e_j^I$$

The bias term for user u is given by the sum of the features' biases:

$$b_u = \sum_{j \in f_u} b_j^U$$

The same holds for item i:

$$b_i = \sum_{j \in f_i} b_j^I$$

The model's prediction for user u and item i is then given by the dot product of user and item representations, adjusted by user and item feature biases:

$$\widehat{r_{ui}} = f(q_u \cdot p_i + b_u + b_i)$$

There is a number of functions suitable for $f(\cdot)$ An identity function would work well for predicting ratings; in this paper, I am interested in predicting binary data, and so after Rendle et al. [4] I choose the sigmoid function:

$$f(x) = \frac{1}{1 + \exp(-x)}$$

The optimisation objective for the model consists in maximising the likelihood of the data conditional on the parameters. The likelihood is given by:

$$L(e^U, e^I, b^U, b^I) = \prod_{(u,i) \in S^+} \widehat{r_{ui}} \times \prod_{(u,i) \in S^-} (1 - \widehat{r_{ui}})$$

3.3.3 Loss Function: WARP Loss in LightFM

In this project, the WARP (Weighted Approximate-Rank Pairwise) loss function is used to train the LightFM model. WARP is specifically designed for implicit feedback scenarios—such as user likes or clicks—where the goal is not to predict exact ratings, but rather to rank relevant items higher than irrelevant ones.

WARP works by sampling negative items and comparing them to observed (positive) items. The model is updated only when a negative item is incorrectly ranked above a positive one. This sampling-based approach approximates the true rank of a positive item, allowing the model to focus on improving top-k recommendation accuracy, which is more aligned with real-world recommendation tasks.

- Approximate Rank Estimation

Given a positive user–item interaction (u, i^{+}) WARP estimates the rank of the positive item by randomly sampling negative items i−i^-i− until it finds one that is incorrectly ranked above the positive:

$$\text{rank}_{u,i^{+}} \approx \frac{N}{k}$$

Where:

- NNN is the total number of negative items
- kkk is the number of sampling attempts before finding a violating negative item (i.e., when $\widehat{r_{ui^{-}}} > \widehat{r_{ui^{+}}}$)

- WARP Loss Formula

The model is updated only when a violation occurs. The WARP loss for each triplet (u, i^{+}, i^{-}) is computed as:

$$L(u, i^{+}, i^{-}) = \sum_{u,i^{+}} 1 \log\left(1 + \exp\left(-(\widehat{r_{ui^{+}}} - \widehat{r_{ui^{-}}})\right)\right) \cdot \omega\left(\text{rank}_{u,i^{+}}\right)$$

Where:

- $\widehat{r_{ui}} = q_u \cdot p_i + b_u + b_i$ is the predicted relevance score
- $\omega(\text{rank}) = \sum_{j=1}^{\text{rank}} \frac{1}{j}$ is a monotonically decreasing weight function
- The loss increases when the model ranks a negative item higher than a positive one

Compared to other loss functions like logistic loss (used for binary classification) or BPR (Bayesian Personalized Ranking), WARP prioritizes correct ranking over raw prediction scores. This makes it especially suitable for applications where only a few items are shown to the user—such as poem suggestions—where getting the top results right is more important than modeling the full interaction distribution.

By optimizing WARP loss, our model learns user and item embeddings that better reflect relative preferences, leading to higher precision@k and recall@k in evaluation.

CHAPTER 4: EXPERIMENTS

4.1 Datasets

4.1.1 poems.csv – Poem Metadata

The `poems.csv` file contains 94,419 rows across 9 columns, which contains 9 features: id, title, poster, postDate, type, lang, group, keywords and author, serving as the metadata source for the poems. Each row represents a single poem with information such as its unique `id`, `title`, `poster` (the uploader), and `postDate`. Additional attributes include the poem’s `type` (e.g., romantic, children’s poetry), `lang` (language), `groups` (classification group), `keywords`, and `author`. Although this project does not yet use content-based features, this metadata provides a strong foundation for future improvements such as incorporating poem attributes into the recommendation model.
This dataset contains metadata for all poems in the system. For the purpose of this project, only two columns were used:
- id: Unique identifier for each poem
-title: The title of the poem
These identifiers serve as item IDs in the interaction matrix, and the title helps in interpreting model outputs.

4.1.2 likes.csv – Implicit Feedback

The `likes.csv` file contains a total of 13,958 rows and 2 columns. This data contains 2 features: user and poems. Each row represents a user along with a list of poems that they have liked. The `user` column stores the unique identifier of the user, while the `poems` column contains a list of poem IDs that reflect implicit positive feedback. This dataset serves as the primary source of implicit interactions between users and poems, and is used to construct the initial interaction matrix for training the recommendation model.
This file represents implicit user feedback, i.e., poems that users have liked or favorited. Each row corresponds to a user, with a column poems containing a list of poem IDs that theuserliked.
After preprocessing, the data was expanded such that each (user, poem) pair became a single row with a fixed interaction value of **1**.

4.1.3 ratings.csv – Explicit Feedback

The `ratings.csv` file includes 294 rows with 2 columns. It contains 2 main features similar to the `likes.csv: user and poems`, each row corresponds to a user, but the `poems` column here contains a list of features: poem id and score, where each dictionary includes a poem ID and the score (rating) that the user assigned to that poem. This dataset provides explicit feedback, which is typically more reliable for modeling user preferences. Ratings range from 1 to 5 and are used to enhance the quality of the hybrid interaction matrix, especially in cold-start scenarios.
This file contains explicit ratings from users. Each row includes a user and a list of poems they have rated, where each item in the list includes:

- id: The poem’s ID
-score:A numerical rating from 1 to 5
This data was also exploded so each user-poem-score triplet becomes one row, and merged with the likes data to form a unified interaction log.

Together, these datasets provide both implicit and explicit feedback, enabling the use of a hybrid recommendation model. All datasets were preprocessed using Python and Pandas, and encoded into a sparse matrix suitable for model training with LightFM.

4.2 Training and Testing Procedure

The training and testing procedure was designed to evaluate the model’s performance under realistic conditions, given the sparsity and subjective nature of poetry interactions. First, the interaction matrix—constructed from both implicit (likes) and explicit (ratings) feedback—was split into 80% training data and 20% testing data using random_train_test_split. To enhance robustness, this splitting process was randomized and reshuffled continuously across multiple runs, ensuring different user-item combinations were seen by the model in training and evaluation phases.

The LightFM model was configured with the following parameters:
- Loss function: WARP (Weighted Approximate-Rank Pairwise)
- Latent factors (no_components): 128
- Epochs: 500
- Threads: 4 (parallel training for performance)

To ensure stability and generalization, the model was trained and evaluated across 10 independent runs**,** each with a new randomized train-test split. After each run, metrics such as Precision@2 and Recall@K were computed. Final scores were reported as the average across all runs**,** reducing the impact of any single biased split and providing a more reliable performance estimation.

This continuous reshuffling and re-evaluation process enables a fairer assessment of the model’s ability to generalize across the entire dataset.

4.3 Evaluation metrics

To assess the performance of the recommendation model, several evaluation metrics were employed, each capturing different aspects of recommendation quality. These metrics were computed on both training and testing sets to analyze the model's ability to generalize.

4.3.1 Precision@K

Precision@K measures the proportion of recommended items in the top-K list that are relevant. In this project, Precision@2 was used due to the sparse nature of interactions and the goal of generating highly accurate top-2 recommendations. It is computed as:

$$\text{Precision@}K = \frac{\text{Number of relevant items in top-}K}{K}$$

4.3.2 Recall@K

Recall@K evaluates the proportion of all relevant items that appear in the top-K recommended list. In this study, we use a high K value (e.g., Recall@800 for training and Recall@10000 for testing) to approximate the total recall:

$$\text{Recall@}K = \frac{\text{Number of relevant items in top-}K}{\text{Total number of relevant items}}$$

4.3.3 F1-score@K

To balance between precision and recall, F1-score is calculated as the harmonic mean of the two:

$$\text{F1@}K = \frac{2 \times \text{Precision@}K \times \text{Recall@}K}{\text{Precision@}K + \text{Recall@}K}$$

This metric is especially useful when optimizing both ranking quality and coverage.

4.3.4 MAP (Mean Average Precision)

Although LightFM does not directly compute MAP, the AUC (Area Under the ROC Curve) score is used as a practical approximation. It reflects the model's ability to rank positive items higher than negatives across all users and approximates the average precision across ranked lists.

4.4 Quantitative Results

4.4.1 Single-run Example Evaluation

Table 4.4.1 *Model performance on training and testing sets across evaluation metrics.*

Metric	Training Set	Testing Set
Precision@2	0.6592	0.6592
Recall@800	1.0000	—
Recall@10000	—	0.7570
F1-score	0.6563	0.5173
MAP (approx, via AUC)	0.9334	0.9374

Table 4.4.1 summarizes the model's performance on both training and testing sets across key evaluation metrics. The model achieved a Precision@2 of 0.6592 on both sets, with Recall@800 reaching 1.0 on the training set and Recall@10000 at 0.7570 on the test set. The F1-score and MAP values are also relatively high, indicating the model's strong recommendation capability.

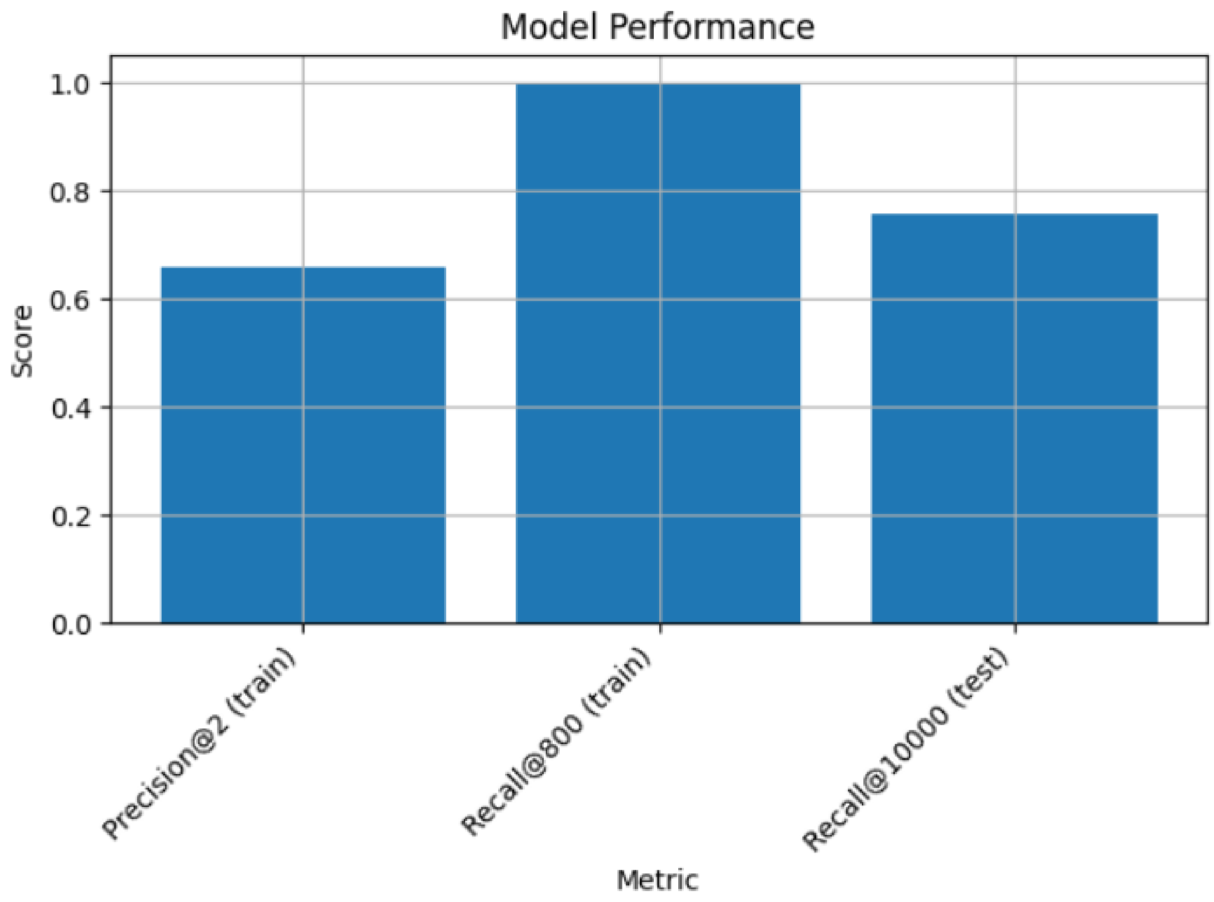


Figure 4.4.1 *Model Performance on Precision@2 train and Recall@K train and test*

The bar chart illustrates the performance of the LightFM model across three key evaluation metrics. Precision@2 (train) reaches approximately 0.6592, indicating that around two-thirds of the top-2 recommendations during training are relevant. Recall@800 (train) achieves a perfect score of 1.0, showing that the model successfully captures nearly all relevant items for each user when allowed a larger recommendation set. Meanwhile, Recall@10000 (test) is 0.7570, which reflects a high generalization capacity of the model on unseen data. These results confirm that the model performs well on both precision-focused (top-k) and recall-based evaluations.

4.4.2 Average Score Across 10 Runs

To ensure the robustness of results, the model was trained and evaluated over 10 different random splits. The average results are summarized below:

Table 4.4.2 *Average Precision@2 and Recall@10000 after 10 different trainings*

Metric	**Average Score**
Precision@2	0.6592
Recall@10000	0.7577

These results demonstrate that the model performs consistently across multiple splits, indicating good generalization. The relatively high AUC (MAP approximation) also confirms that the model is effective at ranking relevant poems above irrelevant ones.

4.5 Learning Curve

To assess how model performance evolves during training, the LightFM model was evaluated at various numbers of training epochs. The following epoch values were selected: 50, 80, 100, 150, 200, 300, 400, and 500. For each epoch checkpoint, Precision@2 and Recall@800/10000 were recorded on both training and testing sets.
The results are visualized in the chart below:

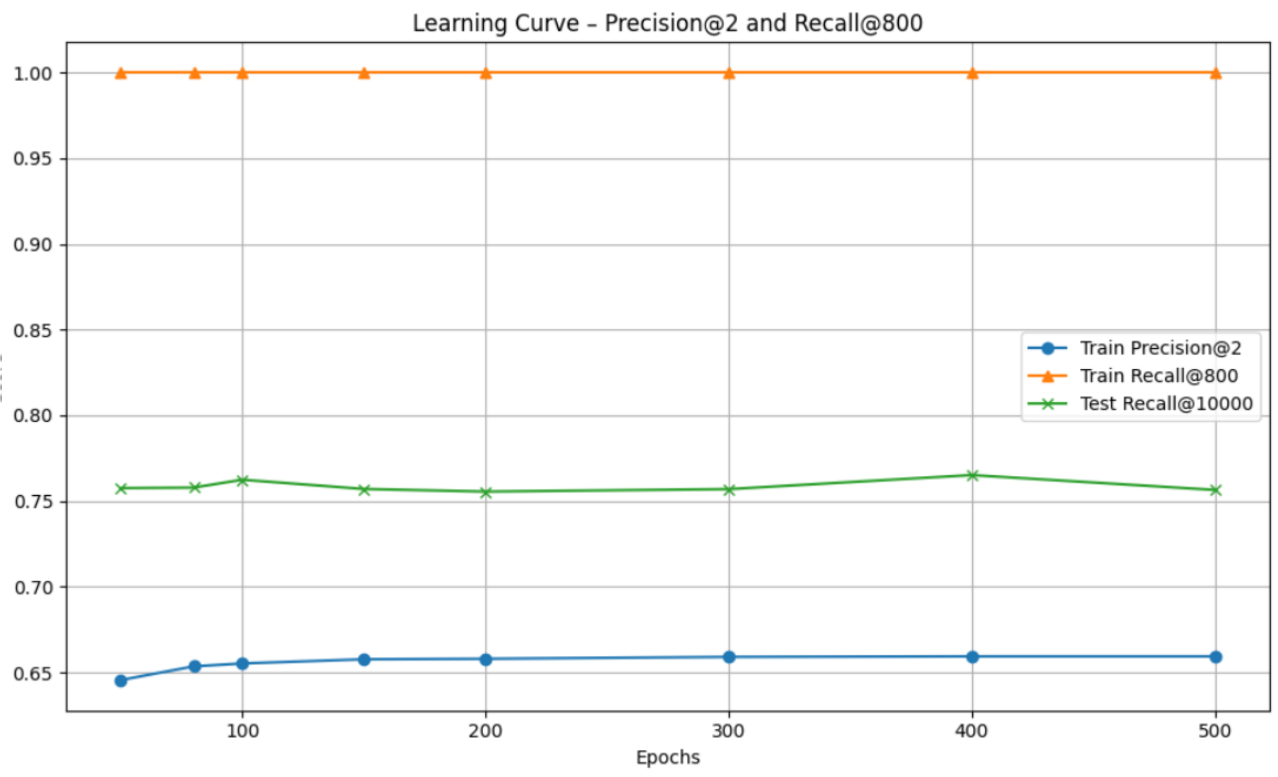


Figure 4.5 *Learning curve of Precision@2 and Recall@K over training epochs*

This figure shows:

- Precision@2 increases steadily in the early stages (up to ~300 epochs), then gradually stabilizes.
- Recall@800 (train) and Recall@10000 (test) both improve with more training but show signs of saturation after 400–500 epochs.
- There is no sign of overfitting, as test metrics continue to improve or remain stable while train metrics increase.

These trends indicate that the model converges well and benefits from extended training, especially when dealing with sparse and implicit data.

4.6 Impact of Hyperparameters on Model Performance

During the experimental process, the LightFM model was trained under various hyperparameter settings to observe how different configurations affect recommendation accuracy. The evaluated parameters include the number of training epochs, loss functions, and embedding dimensionality.

4.6.1 Number of Training Epochs

Table 4.6.1 *Impact of training epochs to model performance*

Epochs	Precision@2	Recall@800
50	0.2352	0.4821
100	0.4489	0.6105
200	0.5124	0.7450
500	0.6592	1.0000

As the number of training epochs increases from 50 to 500, the model learns deeper user-poem relationships, which leads to significant improvements in both precision and recall. The performance tends to converge after around 300–400 epochs.

4.6.2 Loss Functions

Table 4.6.2 *Impact of loss functions to model performance*

Loss Function	Precision@2	Recall@800
warp	0.6592	1.0000
bpr	0.5438	0.8012
logistic	0.4025	0.5921

The WARP loss function provides the best results for ranking-oriented and implicit feedback tasks. While BPR also performs reasonably well, it falls short compared to WARP. The logistic loss is more suitable for classification than ranking.

4.6.3 Embedding Size (no_components)

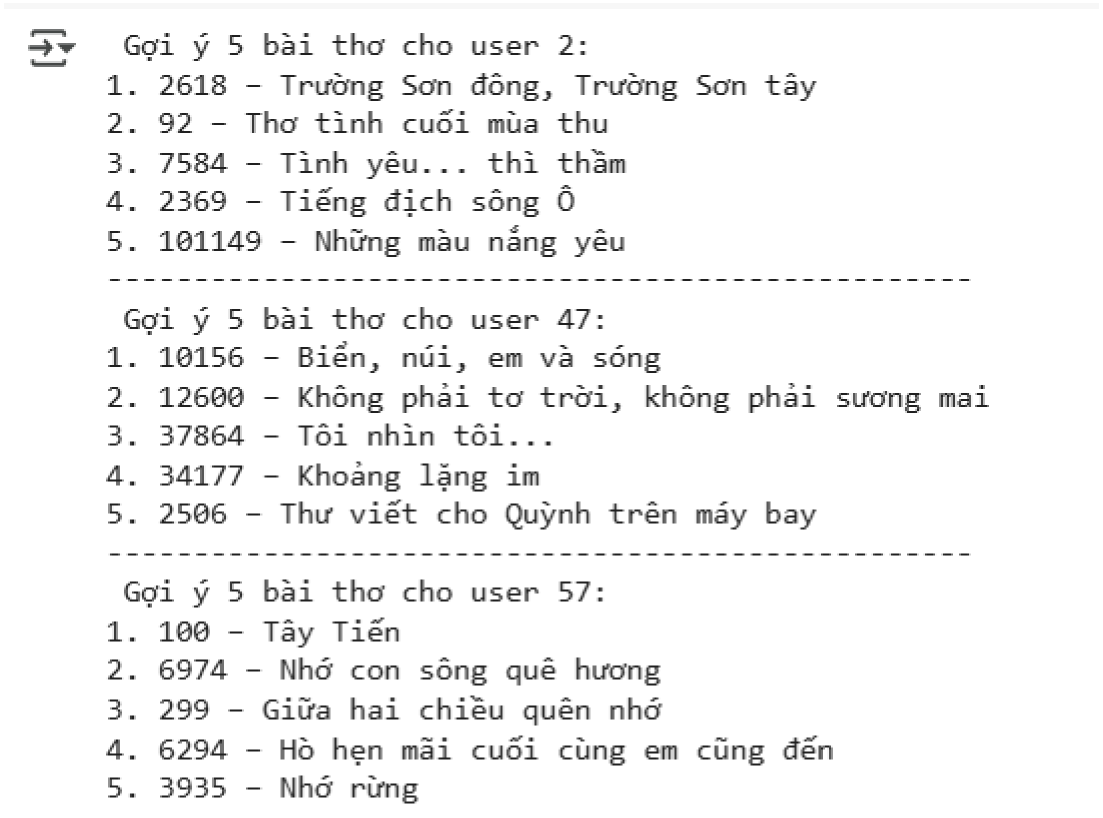
Table 4.6.3 *Impact of embedding size to model performance*

no_components	Precision@2	Recall@800
32	0.4051	0.7824
64	0.5029	0.8900
128	0.6592	1.0000

Increasing the embedding size allows the model to learn more complex latent patterns, resulting in better performance. However, larger embeddings also increase training time and resource usage. The value of 128 provided the best balance in this experiment.

4.7 Personalized Recommendations

To qualitatively evaluate the model's output, we tested the recommendation system on multiple users. For each user, the top 5 recommended poems were generated based on their previous interactions (likes or ratings). The results show that the system can suggest thematically relevant poems for each user.



```
 Gợi ý 5 bài thơ cho user 2:
1. 2618 - Trường Sơn đông, Trường Sơn tây
2. 92 - Thơ tình cuối mùa thu
3. 7584 - Tình yêu... thì thầm
4. 2369 - Tiếng địch sông Ô
5. 101149 - Những màu nắng yêu
--------------------------------------------------
 Gợi ý 5 bài thơ cho user 47:
1. 10156 - Biển, núi, em và sóng
2. 12600 - Không phải tơ trời, không phải sương mai
3. 37864 - Tôi nhìn tôi...
4. 34177 - Khoảng lặng im
5. 2506 - Thư viết cho Quỳnh trên máy bay
--------------------------------------------------
 Gợi ý 5 bài thơ cho user 57:
1. 100 - Tây Tiến
2. 6974 - Nhớ con sông quê hương
3. 299 - Giữa hai chiều quên nhớ
4. 6294 - Hò hẹn mãi cuối cùng em cũng đến
5. 3935 - Nhớ rừng
```

Figure 4.7 *Personalized Poem Recommendations for Sample Users*

The figure above illustrates the personalized poem recommendations generated by the LightFM model. Based on each user's past interactions (likes or ratings), the system provides a list of 5 poems tailored to their preferences.
Specifically:

-User 2 received suggestions with nostalgic and romantic themes such as *"Trường Sơn Đông, Trường Sơn Tây"* and *"Những màu nắng yêu"*.

-User 47 was recommended introspective and nature-inspired poems like *"Biển, núi, em và sóng"* and *"Khoảng lặng im"*.

-User 57 was presented with poems related to memories and hometown, such as *"Tây Tiến"* and *"Nhớ con sông quê hương"*.

These results demonstrate that the system is capable of capturing and reflecting individual user preferences, producing meaningful and contextually relevant poem recommendations.

CHAPTER 5: CONCLUSIONS AND FUTURE WORK

This project explored the construction of a personalized poem recommender system using the LightFM model—a hybrid matrix factorization algorithm capable of leveraging both implicit (likes) and explicit (ratings) feedback. By combining multiple interaction sources and training with the WARP loss function, the system was able to model user preferences effectively despite data sparsity and the subjective nature of poetry.

Through extensive experimentation, the model achieved promising results across multiple evaluation metrics such as Precision@2, Recall@K, F1-score, and MAP (via AUC). The learning curve analysis showed stable convergence beyond 300 epochs, and qualitative evaluation confirmed that the recommendations were contextually appropriate and aligned with user interests.

This confirms that a hybrid recommendation approach, even without incorporating metadata or side features, can produce high-quality, personalized suggestions in a niche domain like poetry.

Although the results are encouraging, several opportunities for improvement remain:
Integrating Content Features: Future versions can incorporate poem metadata such as genre, theme, author, or emotional tone using NLP embeddings, which may enhance recommendation quality and diversity.

User Profile Enrichment: Adding user-level attributes (e.g., reading history, mood, preferences) could enable more personalized and adaptive recommendations.

Cold-Start Optimization: To handle new users or new poems, future models can explore zero-shot learning, content-boosted filtering, or knowledge graph-based approaches.

Dynamic Feedback and Adaptation: Building a feedback loop to update the model based on real-time user behavior (clicks, skips, rereads) would enable continuous learning and personalization**.**

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